Trust as 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 FinTech lenders. The empirical setting exploits the outburst of the Wells Fargo scandal as a negative shock to trust in banks. Using a difference-in-differences framework, I find that increased exposure to Wells Fargo scandal leads to an increase in the probability of using FinTech as a mortgage originator. Survey evidence shows that the increased use of FinTech is due to the erosion of trust in banks. The causal relationship between high exposure to Wells Fargo scandal and high FinTech adoption is more pronounced when individuals have low ex-ante trust in banks and high trust in media, proxied by their political affiliations.

Keywords: FinTech, FinTech Adoption, Trust, Bank Scandal, Belief Heterogeneity, Household Finance

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1 Introduction

Technology innovation has always been twined with the financial industry. New technologies, including artificial intelligence, enable institutions to digitize most of their financial services. Technology innovation, especially in the current wave of FinTech innovation, mostly emerges outside the traditional financial institutions. In the U.S. residential mortgage market, online mortgage origination platform Quicken Loans has overtaken banking juggernauts 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, more than 75% mortgage origination services are performed online, while in others, FinTech services were never used (see figure 1).

Why different regions have different levels of FinTech adoption? This is an essential question because FinTech innovation brings in efficiency and improves social welfare (Fuster et al. (2018)). The potential entry barriers faced by FinTech firms could slow down the progress of technology adoption. In this paper, I try to understand the potential entry barriers to FinTech, specifically, the role of trust in incumbent lenders (banks) as an entry barrier to FinTech lenders.

Trust plays an essential role in the financial market. Lack of trust discourages household stock market participation (Guiso et al. (2008), Giannetti and Wang (2016)). Trust enables incumbent banks to have access to cheaper credit (Thakor and Merton (2018)). The roles trust plays in the financial market give existing financial institutions comparative advantages relative to new entrants. Thus trust in incumbent financial institutions serves as a nature entry barry to FinTech firms. Gallup Analytics surveys "Trust in Institutions" shows that states reporting low "Trust in Banks" have significantly higher FinTech adoption rate (figure 2).

However, trust in banks and FinTech adoption may be jointly determined by unobservable local banking industry shock and local economic conditions. If one region experienced unobservable banking industry shock, the banks' quality of services might deteriorate, and households would be less likely to trust banks. It's 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 negatively correlate with FinTech adoption.

To address the identification threat, I exploit the outburst of Wells Fargo account fraud scandal as a negative shock to households' trust in banks, which is unrelated to any credits shocks or local economic conditions. As one of the most prominent corporate scandals after the financial crisis, the Wells Fargo account fraud scandal included creating millions of fraudulent saving and checking accounts, force-placing collateral and auto protection insurance to customers, and inappropriately charging extension fees. Since most of the fraudulent behavior dated back to as early as 2005, it's unlikely that the fraudulent act was a reaction to FinTech penetration. The news of fraud drawn national attention in late 2016 when federal regulators fined the bank $ 185 million. The timing of the outburst is also unlikely to be correlated with any unobservable local economic shocks.

I use deposits share of Wells Fargo branches to measure county-level household exposure to Wells Fargo scandal. 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. I exploit the revelation of the Wells Fargo account fraud scandal as a negative shock to households' trust in banks in exposed (treated) areas. Moreover, when the Wells Fargo scandal was revealed, households in areas with higher exposure to Wells Fargo scandal would have a more significant decrease in trust in banks, which creates cross-sectional heterogeneity in treatment effect.

I compare 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. Using a difference-in-differences strategy, I find that one standard deviation increase in exposure to the Wells Fargo scandal leads to a 2% increase from the average probability to choose FinTech lender. An increase in the exposure of the Wells Fargo scandal also leads to a decrease in the probability of choosing non-FinTech shadow banks. Although the bank scandal is focusing on Wells Fargo, there exists a significant spillover effect on non-Wells

Fargo banks. Moreover, exposure to the Wells Fargo scandal also increases the use of non-FinTech shadow banks, indicating that erosion of trust in banks will also affect other types of non-bank lenders.

Having established that exposure to bank scandal has a causal effect on the probability of choosing a FinTech lender, I next show that the effect is through the channel of trust erosion in banks. I measure individual trust in banks using Gallup survey data. I find that one standard deviation increase in the exposure to Wells Fargo scandal in a county leads a 10% decrease from the average probability to report trust in banks.

Moreover, I find that the negative relationship between high exposure to Wells Fargo scandal and low trust in banks is more pronounced when individuals have high trust in media and ex-ante low trust in banks, proxied by their political affiliations. Consistent with findings in Gentzkow and Shapiro (2006), Gentzkow et al. (2018), an individual's response to public information is affected by individual' ex-ante belief and the trustworthiness of the information. I utilize this heterogeneity to sharpen my identification strategy in studying FinTech adoption. Gallup survey shows that an individual's trust in media and trust in banks is largely determined by her political affiliation, that non-Republican has higher trust in media and lower trust in banks. Therefore, non-Republican has a higher decrease in trust in banks after exposed to the Wells Fargo scandal. Thus I can use political affiliation to proxy for the magnitude of trust erosion in banks. [1]

By adding a triple interaction of political affiliation, Wells Fargo exposure, and after 2016 indicator, I find that, after exposed to Wells Fargo scandal, counties with more non-Republican voters have a larger increase in FinTech share, comparing to counties with the same level of scandal exposure but more Republican voters. Since non-Republican voters are also more likely to lose trust in banks after exposed to the Wells Fargo scandal, the result validates the argument that exposure to bank scandals affects FinTech adoption through the erosion of trust in banks.

Our conclusions rely on several assumptions. The first assumption is that the level of exposure measured by Wells Fargo deposits share is uncorrelated with unobservable

[1]Here, I use individual political affiliation to proxy for ex-ante trust in banks and trust in media. The idea to use political affiliation to proxy for ex-ante belief also used in Meeuwis et al. (2018).

shock that affects FinTech adoption. Though I can not formally test this hypothesis, if there exists an unobserved shock that only affects an area with high initial Wells Fargo deposit share, we should see that FinTech share evolves differently between treated and less-treated region before the revelation of Wells Fargo scandal.

To address this identification threat, I examine the dynamic effects of exposure to the Wells Fargo scandal on trust in banks and FinTech adoption. I find that both trusts in banks and FinTech adoptions are not different between treated regions and less-treated regions before the scandal.

The second 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 shock, FinTech adoption may increase because banks in area with more exposure to Wells Fargo scandal reduced credit supply after the scandal.

To rule out the credit supply channel, I examine both bank deposits and mortgage reject rate. I find that exposure to the Wells Fargo scandal has a minimal effect on bank deposits. Since deposit is the most critical funding source for banks, banks do not have to reduce credit supply because of financial constraints. I then find that for most types of lenders, the percentage of mortgage rejected by lenders does not change after exposure to Wells Fargo shock. Moreover, though I show that after exposed to Wells Fargo scandal, counties with more non-Republican voters have a larger increase in FinTech share, it is possible that the increased FinTech share is due to more decrease in credit supply rather than more erosion of trust in counties with larger share of non-Republican voters. I rule out the alternative channel by showing that high non-Republican share treated counties do not experience credit supply reduction by banks. So our results are unlikely to be driven by a reduction in credit supply.

This paper contributes to the literature in financial technology, the role of trust in finance, and the entry barrier to new firms.

Fuster et al. (2018) show that FinTech lenders originate mortgage faster and screen borrower more effectively, originate 20% faster than other lenders and have 35% lower default rate in FHA loans. Tang (2018) studies the clientele of the P2P platform, concluding

that P2P lending substitute bank lending, by showing that average P2P borrower quality dropped after a negative shock to bank credit supply. Buchak et al. (2018) shows that technology advantages contribute to the growth of FinTech lending. This paper contributes to the literature by studying the cross-regional difference in FinTech adoption and help us understand the potential disproportionate effect of FinTech adoption.

A large amount of literature has documented the role of trust in finance. Guiso et al. (2004) show that social capital plays a key role in the financial development. Giannetti and Wang (2016) find after the revelation of corporate fraud in the state, household reduces their participation in the stock market due to the erosion of trust. Thakor and Merton (2018) argue that trust enables banks to have access to cheaper credit. This paper documents that trust also plays a vital role in the newly introduced FinTech market.

Bertsch et al. (2020) use Consumer Financial Protection Bureau complaint data to proxy for bank misconduct, finding a positive association between bank misconduct and the usage of online lending. This paper takes up the challenge of assessing whether bank scandal correlates with FinTech adoption due to bad banking market shocks or bank scandal affects FinTech adoption through decreased trust in banks.

Moreover, this paper documents that household belief heterogeneity could affect household finance decision. It enriches the line of research documenting the relationship between household belief and (optimal) finance decisions, e.g. D'Acunto et al. (2019), and Meeuwis et al. (2018).

Incumbent firms use various strategies to deter the entry of new firms. Milgrom and Roberts (1982) show that incumbent firms build a predatory reputation to prevent firm entry. Cunningham et al. (2019) document that incumbent firms acquire innovative targets to discontinue the innovation, which they call "Killer Acquisition". I contribute this line of research by showing that incumbent financial firms can use the trust to deter entry.

The paper proceeds as follows. Section 2 describes the data. Section 3 discusses the empirical methodologiy. Section 4 presents the results and robustness tests, and section 5 concludes the paper.

2 Data Source and Main Variables of Interest

2.1 Define FinTech Lenders

The definition of FinTech lender is central to our research question. Following existing literature studying FinTech lending in the residential mortgage origination market (Buchak et al. (2018), Fuster et al. (2018)), I define FinTech lender as a non-depository institution in which provide full-scale, comprehensive online mortgage origination services. A lender is classified as either a bank or a shadow bank. A bank is defined as a depository institution, and a shadow bank is defined as a non-depository institution. Shadow lenders are then categorized into FinTech lenders and non-FinTech shadow banks. FinTech lenders are those whose mortgage origination process can be completely done online.

The first key feature in the definition of FinTech is the scope of technology innovation. The lenders' ability to process whole mortgage origination online represent 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. In the "back-end", software and algorithm have been developed to process and verify the information from the documents. For example, the system can identify potentially fraudulent applications by flagging inconsistent data. Such a degree of automation reduces information process time and labor intensity.

Though 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. [2] One caveat is that some companies classified as non-FinTech lenders in 2017 fitted into the definitions of FinTech lender in 2018. Though such transition may be correlated with trust erosion in banks, I do not classify these lenders as FinTech in my main analysis. Mostly because it happened nearly two years after the

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

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. The robustness tests classifying these as FinTech are provided in the appendix.

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

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

The number of loans can be either number of loan originations or the number of total loan applications. HMDA tracts all mortgage loan applications, including originated loans and denied loans. [3] To define FinTech adoption at the county level, one can use either number of total applications or only originated loans. 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 interesting when examing 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 level of FinTech adoption. When we consider improved efficiency brought by the FinTech revolution, this measure is what matters. 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 give similar results.

I use the number of loans instead of the total dollar amount to be consistent with loan-level analysis. The results using the total dollar value of loans are provided in the appendix.

2.2 U.S. Residential Mortgage Data

Home Mortgage Disclosure Act (HMDA) requires all depository and non-depository lenders to disclosure information on housing-related loans. I use HMDA loan-level mortgage application data. This dataset covers the majority of home mortgage applications in the U.S.

[3] HMDA also includes loans withdrawn, and other types of actions.

and has been the most important data source studying FinTech adoption in the residential mortgage market. The dataset provides information including, lender name, year of application, property location, application outcome, loan amount, loan type, loan purpose, loan purchaser type, and gender, income, race, and ethnicity of applicant(s).

Application outcome is named as "Type of Action" in 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)". Loan origination is defined as "Type of Action" equalling to "Loan Originated".

A direct measure of household demand for mortgage 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. So I exclude "loan purchase" when measuring total applications. Besides, 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 the real intention of mortgage demand. Also, FinTech lenders are online lenders and are convenient to apply to. Naturally, there will be more "File closed for incompleteness" cases. To avoid confusion, I do not include those records in "total applications".

Fannie Mae single-family loan performance dataset provides origination and performance data on a subset of Fannie Mae's 30-year and less, full-documentation, single-family, conventional fixed-rate mortgage. The origination (acquisition) dataset provides information including, 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 in-

[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.

come ratio, borrower FICO score, first three digits of the property's zip code. Sellers' names are available only for entities that represent 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 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 until 2017.

Despite documented 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 regulators. Following Giannetti and Wang (2019), I plot the Google trend of search topic "Wells Fargo Account Fraud Scandal" and topic "Wells Fargo Scandal", as a measure of time series trend of the public attention. The Google search index is normalized to 100, which is the index value when the topic has the highest volume of search intensity. The highest search intensity arrived in Sept 2016 when the regulators issued the enforcement actions. I since conclude that households are exposed to Wells Fargo scandal after 2016, in particular, after the third quarter of 2016. One concern about this national-wide attention is that California might have some pre-exposure to the Wells Fargo scandal due to news reported by *Los Angeles Times*. So I only include Google search from users in California. Figure 3 shows that there aren't significant differences in Google search intensity between California and other states.

Establishing 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-region differences in 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 oper-

ates more intensively, local media would also be more likely to pay attention to the scandal, which intensifies the effect.

Deposits data is from Federal Deposit Insurance Corporation(FDIC) The 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 deposits as of June 30 in that branch.

I measure county-level household exposure to Wells Fargo scandal by the Wells Fargo deposit share in June 30 2015.[5] For each county, the Wells Fargo deposits share is calculated as the total amount of deposits in Wells Fargo branch in that county over the total amount of deposits by all FDIC insured institution,

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

Another way to measure the cross-regional differences is to use the geographic variation of public attention in the Wells Fargo scandal, which can be measured using Google Trend data. Google trend provides a state-level index called "Interest by subregion". The index is on a scale from 0 to 100. 100 indicates the state with most search intensity, while 0 indicates that there was not enough data for the topic or term. I measure state-level attention to "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. Comparing to figure 4, public attention mostly concentrated in states with high Wells Fargo deposits share. People in states without Wells Fargo branch did not pay attention to the Wells Fargo scandal. I use 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 Gallup Analytics surveys "Trust in Institutions". In the surveys, Gallup Analytics randomly interviewed around 1000 individuals across the U.S.

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

about their confidence in U.S. institutions, from 1981 to 2018. In addition, 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 reported their confidence in institutions in five scales: "a great deal", "a lot", "very little", "some", or "none". I define dummy variable "Trust in Banks" equaling to one hundred if the individual reported level of confidence in banks as "a great deal" or "a lot", zero otherwise. The same definition applies to "Trust in Big Business", "Trust in Newspapers", and "Trust in Television News". There is no direct survey question asking about confidence level in U.S. media, I take the average trust level of newspaper and TV news as a proxy for trust in media.

Respondents were asked to report their political affiliation as "Republican", "Lean Republican", "Independent", "Lean Democrat", or "Democrat". I define dummy variable "Non-Republican" equaling to one if respondents reported their party affiliations as "Independent", "Lean Democrat", or "Democrat".

2.5 Other Variables

I obtain county-year level demographic data from the US Census American Community Survey(ACS) 1-year estimates 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. Robustness results including all counties are provided in the appendix.

County-level political affiliation data is from MIT Election Data and Science Lab[6]. The dataset includes county-level returns for the 2016 presidential election. County-level total votes, votes for Democratic, Republican, and independent candidates are provided. I measure party affiliation for Non-republican as the total share of votes for Democratic and independent candidates.

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

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. Though figure 2 shows that FinTech adoption is faster in states with lower trust in banks, trust in banks and FinTech adoption may correlate with both unobservable local banking industry shock and local economic condition. If one region experienced unobservable banking industry shock, the banks' quality of services might deteriorate, and households would be less likely to trust banks. It's 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 negatively correlate with FinTech adoption.

I exploit the revelation of the Wells Fargo account fraud scandal as a negative shock to Trust in Banks. As one of the most prominent corporate scandals after the financial crisis, the Wells Fargo account fraud scandal included creating millions of fraudulent saving and checking accounts, force-placing collateral and auto protection insurance to customers, and inappropriately charging extension fees. Most of the fraudulent behavior dated back to as early as 2005, it is unlikely that the fraudulent conduct was a reaction to FinTech penetration. The news of fraud brought national attention in late 2016 after federal regulators fined the bank $ 185 million. The timing of the revelation of the scandal is also unlikely to be correlated with any local economic shocks.

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 high initial Wells Fargo deposit share to an area with low 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,

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

In the loan-level analysis, the dependent variable is an indicator variable equaling to 100 if the mortgage lender is a FinTech lender. In the county-level analysis, the dependent vari-

able is the share of mortgage originated by FinTech lenders. WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is dummy equalling to 1 after 2016. I include county and time fixed effects. County-level control variables are from Buchak et al. (2018), which I will discuss when presenting the results. Since 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.

The parameter of interest β measures the incremental effects of household increased exposure to Wells Fargo scandal on the propensity to choose 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 shock that affects FinTech adoption. Though I can not formally test this hypothesis, if there exists an unobserved shock that only affects an area with high initial Wells Fargo deposit share, we should see FinTech share evolved differently between treated and less-treated region before the revelation of Wells Fargo scandal. In other words, the location of Wells Fargo branches and share of deposits are nearly randomly assigned.

The second assumption is that exposure to the Wells Fargo scandal affects FinTech adoption only through decreased trust in banks. Even if we assume that exposure to the Wells Fargo scandal does not correlate with unobserved local shock, FinTech share may increase because banks in area with more exposure to Wells Fargo scandal reduce credit supply after the scandal. We will rule out this channel by showing that both total deposits and mortgage acceptance rate does not change.

4 Results

4.1 Revelation of Wells Fargo account fraud and FinTech adoption

I first relate the exposure to the Wells Fargo scandal to FinTech adoption, comparing FinTech adoption in areas 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 a difference-in-differences model specified in equation (1).

Table 2 shows that increased exposure to Wells Fargo scandal leads to an increase in the probability of choosing a FinTech lender. Regressions in column (1) (2) (3) only include originated loans and in column (4) (5) (6) include all applications (originated + denied loans). Total application of mortgage loans is a direct measure of household ***demand*** for different types of mortgage lenders. Total number of originated mortgage is a result of both credit supply and demand. Following existing literature on FinTech adoption (Buchak et al. (2018), Fuster et al. (2018), Tang (2018)), I measure FinTech adoption using both loan origination and total application. Later I will show that lender's credit supply does not affect our results.

Column (1) shows that increased exposure to Wells Fargo scandal leads to an increase in the probability of choosing a FinTech lender. One standard deviation (10.4) increase in the exposure to Wells Fargo scandal in a county leads to a 0.15-percentage-point decrease in the probability to choose FinTech lender, which is a 2% increase from the average probability to choose FinTech lender, (7.6). The result is significant at 1% significant level. Since individual characteristics and types of loans may also affect lender choice. I include applicant and loan characteristics in the regression. Females are less likely to choose FinTech lenders than males. People with Hispanic backgrounds are less likely to choose FinTech lenders. Comparing to While people, Asians and African Americans are also less likely to choose FinTech lender.

Since some local economic and market conditions may also affect the probability of choosing a FinTech lender, I add some county-level economic controls from American Community Survey one-year estimates. We lose some observations since the county-year level economic data is 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. [7]. Column (2) shows that increased exposure to the Wells Fargo scandal has positive and significant effects on the probability of choosing a FinTech lender, even controlling for county-level demographics, economic conditions, and local credit market conditions. The economic magnitude is similar.

In column (3), 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 that one standard deviation (32.4) increase in the exposure to Wells Fargo scandal in a county also leads to a 0.2-percentage-point decrease in the probability to report trust in banks, the magnitude of which is similar to exposure measured using Wells Fargo deposit share. This result corroborates that these two are both valid measures of exposure to the Wells Fargo scandal.

As mentioned earlier, those results may be driven by the credit supply of banks. Column (4) (5) (6) show results for using all mortgage loan applications to measure FinTech adoption. The coefficients are all significant and have values similar to results for loan origination. These results show that the effects of exposure to the Wells Fargo scandal on FinTech adoption are not driven by the change of credit supply. Additionally, I later show that lenders' credit supply is not affected by exposure to bank scandal.

Parallel Trend Concluding that exposure to the Wells Fargo scandal causes an increase in FinTech adoption requires the assumption that location and scale of Wells Fargo branches are randomly assigned. If not, the results may be driven by the different trends of FinTech adoption among areas with different Wells Fargo scandal exposure. If so, we should see FinTech share evolved differently between treated and less-treated regions before the revelation of the Wells Fargo scandal. To rule out the alternative channel, I estimate dynamic

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

treatment effect models, in the following forms,

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

WF Exposure is the share of Wells Fargo deposits in county c in 2015. Post is dummy variable equaling to one after 2016. The model is fully saturated by leaving out the year 2015 dummy.

Table 3 shows the dynamic effects of exposure to the Wells Fargo scandal on FinTech adoption. The treatment dynamics are consistent with our assumption. The increase of FinTech adoption only happens in the treated area after the scandal. There exist no pre-trends before the scandal. The magnitudes of treatment effects are similar in year 2017 and year 2018. The results indicate that the Wells Fargo deposits in county c in 2015 is orthogonal to potential confounding unobservable shock, and can be perceived as randomly assigned in this setup.

Choice of other lenders Previous results show that there exists a causal relationship between exposure to the Wells Fargo scandal and FinTech adoption. However, it is not clear which types of lenders failed to retain the borrowers after exposed to the Wells Fargo scandal. I conduct similar empirical analysis on other types of lenders, including Wells Fargo banks, Non-Wells Fargo (Non-WF) banks, all banks, Non-FinTech shadow banks, and all shadow banks.

Table 4 shows that one standard deviation increase in the exposure of Wells Fargo scandal leads to $0.02 * 10.4/43.22 = 0.5\%$ decrease in the probability to choose non-Wells Fargo banks, $0.03 * 10.4/44 = 0.7\%$ decrease in the probability of choosing non-FinTech shadow banks. Recall that the probability of choosing FinTech lenders decreases 2%. Although the bank scandal is focusing on Wells Fargo, there exists a significant spillover effect on non-Wells Fargo banks. However, the magnitude of the effect is much weaker than that on Wells Fargo. Moreover, exposure to the Wells Fargo scandal also increases the probability of choosing non-FinTech shadow banks, indicating that erosion of trust in banks will also affect other types of non-bank lenders.

4.2 The Revelation of Wells Fargo account fraud and Trust in Banks

Having established that exposure to bank scandal has a causal effect on the probability of choosing a FinTech lender, I next show that the effects are through the erosion of trust in banks. Using a similar difference-in-differences model shown in equation (1), I first estimate the effects of exposure to bank scandal on trust in banks.

Following Guiso et al. (2008), I define trust as the subjective probability to be cheated attributed by individuals. I measure individual trust in banks using Gallup survey data. In the empirical analysis, 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, I am not able to identify individual responded repeatedly in different years. I control for individual characteristics and compare individuals reported trust in banks before and after the scandal. Though I cannot control for individual fixed effects, controlling for a wide range of respondent characteristics helps rule out most individual effects on trust in banks.

Column (1) of table 5 shows that exposure to bank scandals leads to a decrease in the probability of reporting trust in banks. A one standard deviation (10.4) increase in the exposure to Wells Fargo scandal in a county leads to a three-percentage-point decrease 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 drive away the results.

Deteriorating county income negatively correlates to lower trust in banks, implying that trust in banks is related to local economic conditions. Moreover, Giannetti and Wang (2016) uses confidence in big business to proxy for trust in the stock market, which relates to the household's stock market participation. In column (4) (5) (6), I re-do all analyses using trust in big business as dependent variables. The results show that exposure to the Wells Fargo

scandal does not cause a decrease in trust in big business, confirming that decreasing trust in banks after exposure to the scandal is not a pure reflection of general trust. Furthermore, the results are not driven by households' other financial decisions.

Moreover, 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. The effect is far from negligible. Survey evidences show that people behave extremely heterogeneously in terms of their trust in banks, which will be further investigated in the next section.

4.3 Heterogeneous effects of scandal on Trust in banks

This section investigates the heterogeneous effects of the Wells Fargo scandal on trust in banks. A large amount of literature has documented the role of belief differences in household's financial decisions (Meeuwis et al. (2018), Giglio et al. (2019)). Furthermore, Meeuwis et al. (2018) uses political affiliation to measure ex-ante heterogeneity beliefs of investors. Results in table 1 and table 5 indeed 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. These different prior beliefs on the trustworthiness of banks may lead to their different responses to the Wells Fargo bank scandal. I re-run analyses in table 5, but split the sample into different groups, by their political affiliations.

Column (1) in table 6 shows that for Non-republican respondents, a one standard deviation (10.4) increase in the exposure to Wells Fargo scandal leads to a 4.5-percentage-point decrease in the probability to report trust in banks, which is a 17% decrease from the non-Republican's average probability to report trust in banks (26.1). On the other hand, column (6) shows that average Republican respondents did not respond to exposure to Wells Fargo scandal. Even controlling for respondent characteristics, column (2) and (7) still show that non-Republican and Republican response to bank scandal differently.

The results in table 6 indicate that people with different party affiliations respond to the Wells Fargo scandal differently, and the different responses may be due to that Republican and non-Republican have different priors on how trustworthy banks were. Theoretically, trust in banks will decrease for households after exposure to the bank scandal, while the magnitudes of such decreases have no definitive prediction. To better understand why average Non-Republican household reduces their trust in banks while the average Republican household does not respond to the Wells Fargo scandal, I further split the samples into groups with different trust in media.

Since he Wells Fargo scandal is most covered by national and local media, how much the households trust media is vital when they update their beliefs about the trustworthiness of banks. The role of media in shaping household beliefs have been documented in various settings (Gentzkow and Shapiro (2006) and Gentzkow et al. (2018)). [8] Take an extreme case, if an individual does not trust the information resources at all, he/she will not change his/her trust in banks even after exposed to the Wells Fargo scandal.

I divide each sample into three sub-groups. Column (3) (8) are individuals with high trust in media (≥ 70), column (4) (9) are median trust in media ($< 70, \geq 50$), and column (5) (10) are individuals with low trust in media (< 50). Since on average non-Republicans have higher trust in media than Republicans, there are more observations in column (3), (4) than in column (8), (9). I then examine the effects of Wells Fargo scandal among these subgroups.

Column (3) shows a one standard deviation increase in the exposure to Wells Fargo scandal leads to an 11-percentage-point decrease in the probability to report trust in banks, for non-Republicans with high trust in media, column (4) shows a 6.6-percentage-point decrease for non-Republicans with median trust in media. The DID coefficient is not significant for non-Republicans with low trust in banks in column (5). The results are consistent with the prediction that individual with higher trust in media responses to bank scandal more.

[8] Though Gentzkow and Shapiro (2006) and Gentzkow et al. (2018) argue that a Bayesian agent will infer that the information source is more trustworthy if the information conforms agent's prior belief when an individual is uncertain about the quality of the source. It is unlikely that bank scandals drive the Republican's low trust in media.

In column (8), for Republicans with high trust in media, a one standard deviation increase in the exposure to Wells Fargo scandal leads to a 31-percentage-point decrease in the probability to report trust in banks, which is three times as big as the effects on non-Republicans with high trust in media. This is not a surprising result. If an agent has full trust in information resources, and her prior is different from the signal, her belief would update much more than the agent whose prior belief is similar to the signal. [9]

On average, Republicans have higher trust in banks, but why don't they react more to bank scandal than non-Republicans. Column (9) (10) show that exposure to the Wells Fargo scandal does not affect trust in banks for Republicans with median and low trust in media. Result in column (10) is consistent with the result in column (5), individuals with low trust in media does not respond to the Wells Fargo scandal. Moreover, comparing to non-Republican with median trust in banks, Republican with median trust in banks does not react to bank scandal. As documented in Gentzkow and Shapiro (2006) and Gentzkow et al. (2018), a Bayesian agent will infer that the information source is more trustworthy if the information conforms agent's prior belief when the agent is uncertain about the quality of the source. Since both groups are uncertain about information quality (median trust in media), Republican respondents may infer that the information is not trustworthy since it contradicts with its prior, thus will not respond to the scandal.

Since the Wells Fargo scandal coincides with the 2016 US presidential election, and Meeuwis et al. (2018) documents that, compared to Democratic investors, Republican investors rebalance their portfolios to riskier assets after the unexpected outcome of the US 2016 national election, and the rebalancing behavior is driven by Republican and Democrats' different updating of beliefs about the future of the US economy. Is it possible that the results are also driven by the different updating of beliefs about the future of the US economy? I argue that since results in table 6 exploits a difference-in-differences setup, the effect from updating beliefs about the future of the US economy are differenced out by the before-after estimator.

Overall, we see that non-Republican reacts more to Wells Fargo scandal than Republi-

[9] One may worry that individuals with high trust in banks does not distribute evenly across different groups with different trust in media. The average trust in banks in group (8) is 54 while the average trust in banks in group (3) is 42, group (8) indeed has higher trust in banks.

cans; the results come from a combination two effects of, (1) Republican and non-Republican have different trust in information resources related to Wells Fargo scandal, (2) Republican and non-Republican have different prior on how trustworthy banks were. Though for Republicans with high trust in media, the effect is significant, but the number of Republicans individual who reports high trust in media is minimal. So, on average, non-Republican reacts more to the Wells Fargo scandal than Republicans. I emphasize that, here, political affiliation is just a **proxy for** two dimensions in the spectrum of trust, trust in media and ex-ante trust in banks.

4.4 Heterogeneous effects of scandal and FinTech Adoption

In the previous section, I document heterogeneous effects of the bank scandal on trust in banks. I now utilize this heterogeneity to sharpen the identification strategy in studying the effect of the Wells Fargo scandal on FinTech adoption. Comparing to individuals affiliated with the Republican party, individuals not affiliated with the Republican party, which proxies for high trust in media and low ex-ante trust in banks, lost more trust in banks after exposing to Wells Fargo scandal. If Wells Fargo scandal affects FinTech adoption through erosion of trust in banks, individual leaning towards Democrats is more likely to choose FinTech lenders, comparing to others with the same level of scandal exposure.

Neither HMDA nor any other mortgage origination datasets report party affiliation of the originator. Thus it is unable to identify the exact party affiliation of 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 high share of non-Republican votes have a higher probability of holding beliefs similar to non-Republican, thus more likely to be affected by bank scandal. I measure county-level FinTech adoption using the share of loans by FinTech lenders. Consistently with loan level analysis, I analyze both loan application and loan origination. The empirical specification is the following,

Triple Interaction

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

where the dependent variable is county-level FinTech share. $WFExposure_c$ is the share of Wells Fargo deposits in county c in 2015. $Post_t$ is dummy equaling to 1 after 2016. $NonRep_c$ is the percentage of votes for Non-Republican candidates in the 2016 presidential election.

The interaction term $WFExposure_c \times Post_t$ captures the average change of FinTech share for all counties exposed to the Wells Fargo scandal in the years after the scandal. Since the Wells Fargo scandal coincides 2016 national election, it is possible that different updating of beliefs about the future of the US economy may affect FinTech adoption. Including term $NonRep_c \times Post_t$ allows to tease out the potential confounding change of 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 $WFExposure_c \times Post_t \times NonRep_c$. β captures the additional change of FinTech share for counties with high non-Republican share.

Table 7 presents results adding triple interaction. Column (1) shows the effect on FinTech adoption measured using mortgage origination. The coefficient is significant and has a value of 0.058. In this setup, one standard deviation (10.4) increase in the exposure to Wells Fargo scandal for a non-Republican individual leads to a 0.6-percentage-point increase in the probability of choose FinTech lender, which is roughly $0.6/6.94 = 9\%$ increase in the probability of choosing FinTech lender. The effect is similar when FinTech share is measured using mortgage application, and stronger than the average effects reported in Table 2.

In column (2) (3) and (5) (6), I exploit the heterogeneity by conducting difference-in-differences analyses in sub-groups. The sample is split into counties with high non-Republican share $(\geq 45\%)$ and with low non-Republican share. Column (2) shows the

result for high non-Republican share counties; the coefficient on the DID term is significant and has a value of 0.014. The magnitude is smaller than that of column (1), because high non-Republican share counties do not have 100% of non-Republican voters. The result is similar in column (5). The DID coefficients in column (3) and column (6) are not significant, indicating that the heterogeneous effect is not perfectly linear. The Wells Fargo scandal possibly only affected FinTech adoption for people who have strong trust in media, and very low ex-ante trust in banks. Results in table 7 corroborate that exposure to bank scandal affects FinTech adoption through the erosion of trust in banks.

4.5 Robustness

Supply of credit One underline assumption for the identification is that exposure to the Wells Fargo scandal affects FinTech adoption only through decreased trust in banks. Even conditioning on that exposure to Wells Fargo scandal is uncorrelated with unobserved local shock; FinTech share may change because banks in area with more exposure may reduce credit supply after the scandal. We rule out this interpretation by showing that both mortgage acceptance rate and total bank deposits do not change.

Table 8 shows that the percentage of mortgage rejected does not change after exposure to Wells Fargo shock, which helps rule out the credit supply channel. In column (3), the reject rate for non-Wells Fargo banks decreases slightly after exposure to the Wells Fargo scandal. However, in column (4) the reject rate for all bank remains almost unchanged. For credit-supply channels to affect FinTech adoption, the only rejection rate matters is that of all banking sectors. It does not matter even there is a slight shift from Wells Fargo to non-Wells Fargo banks within the banking sector. Also, since the effect of exposure to the Wells Fargo scandal on FinTech adoption is also significant when FinTech shares are measured using all mortgage applications, this slight decrease in reject rate does not affect the overall interpretation.

Bank Deposits Traditional banks retain more than 30% of mortgage originated in their balance sheet. So deposit is one key factor affecting the credit supply of banks. 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 9 shows how the exposure to Wells Fargo scandal affects per capita deposits of Wells Fargo, and per capita deposits of all banks.

Exposure to the Wells Fargo scandal has minimal effects on bank deposits. All coefficients are insignificant except in column (3). The log value of deposits for non-Wells Fargo increases slightly, though deposits per capita in column (6) show no change. Deposits may shift from Wells Fargo to non-Wells Fargo after the scandal; however, total deposits in the banking sector did not change. This result is consistent with what we find in table 9, total credit supply from banks did not change. 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.

5 Conclusion

In this paper, I analyze the role of trust in incumbent financial institutions in deterring new entrants with innovative technology. Increased exposure to Wells Fargo scandal leads to an increase in the probability of choosing a FinTech lender. Using Gallup Survey data to measure trust in banks, I show that exposure to the Wells Fargo scandal affects FinTech adoption through the erosion of trust in banks. Moreover, the negative relationship between high exposure to Wells Fargo scandal and low trust in banks is more pronounced when respondents have high trust in media and low ex-ante trust in banks, which are proxied by their party affiliations.

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 share compared to others with the same level of scandal exposure. Since non-Republic respondents reduce 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.

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Figures

Figure 1: Heterogeneity in FinTech Adoption

This figure displays county level FinTech adoption rate measured by share of mortgage originated by FinTech lenders in 2017.

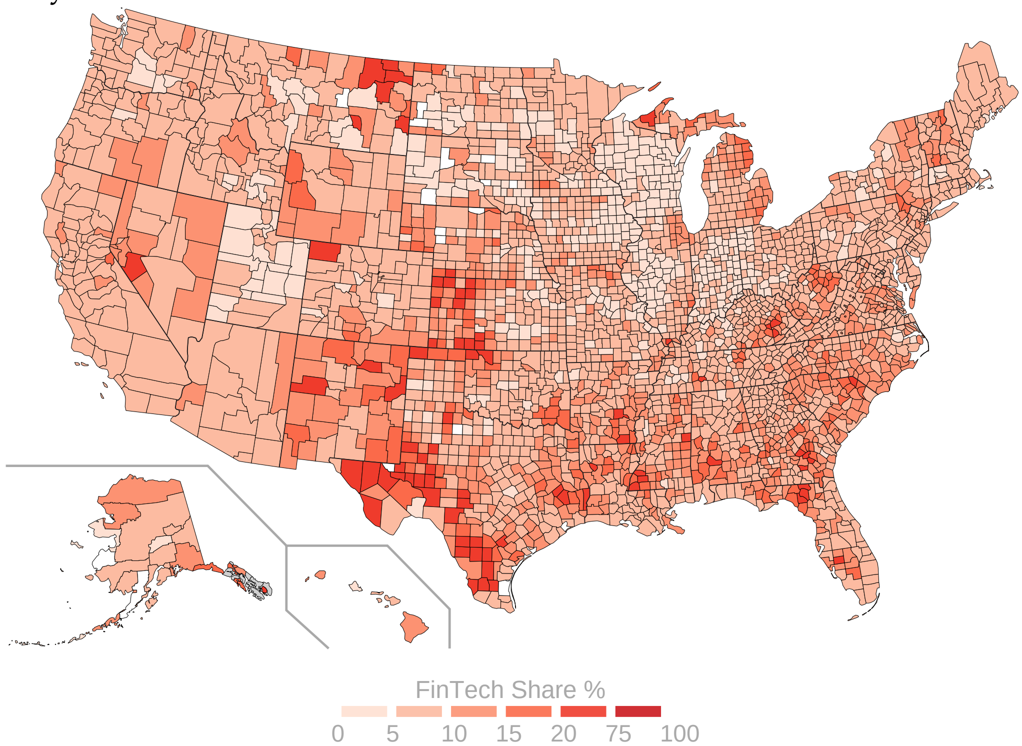

Figure 2: FinTech Adoption in Low and High "Trust in Banks" States

This figure plots 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 larger than median (27%). FinTech share is measured as number of loans originate by FinTech lenders. Time series plots of FinTech share are provided for both loan originations and loan applications.

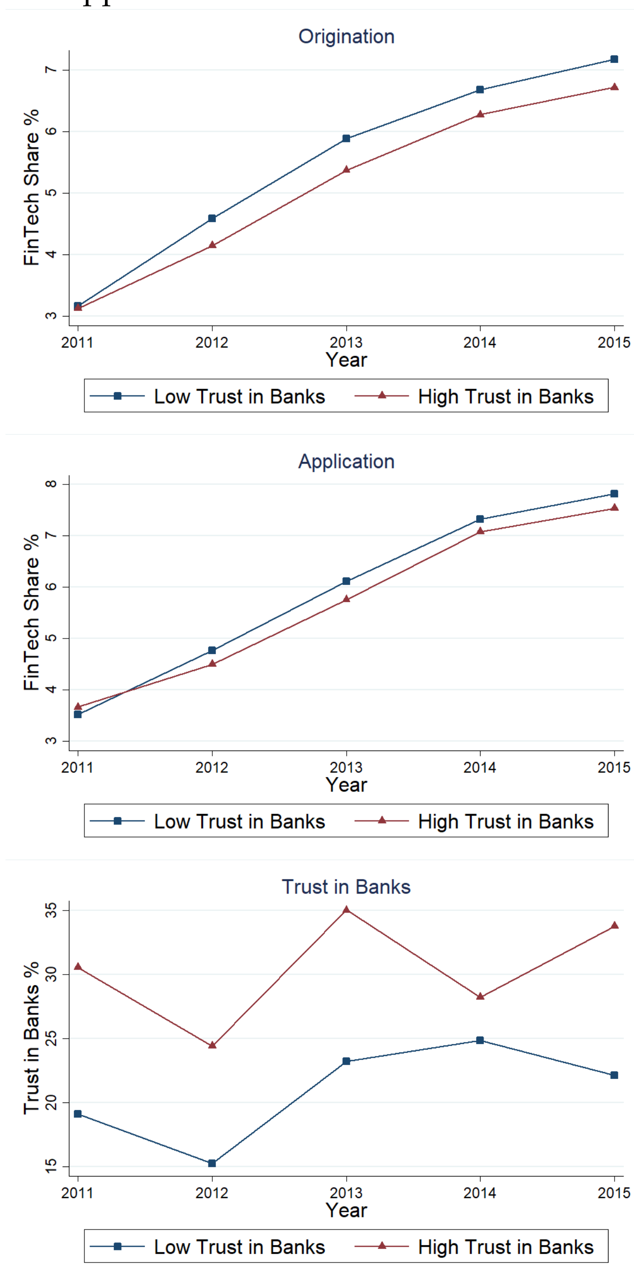

Figure 3: Google Search Intensity Trend of Wells Fargo Scandal

This figure displays trends Google search intensity and Daily Newspaper Coverage of Wells Fargo scandal from 2013 Jan to 2018 Dec. The first row shows the google search volume of Topic "Wells Fargo Account Fraud Scandal", from U.S. users (left) and Californian users (right) respectively. The second row shows the google search volume of term "Wells Fargo Account Fraud Scandal", from U.S. users (left) and Californian users (right) respectively. The last row shows number of "Wells Fargo scandal" related newspaper articles in U.S. daily newspaper.

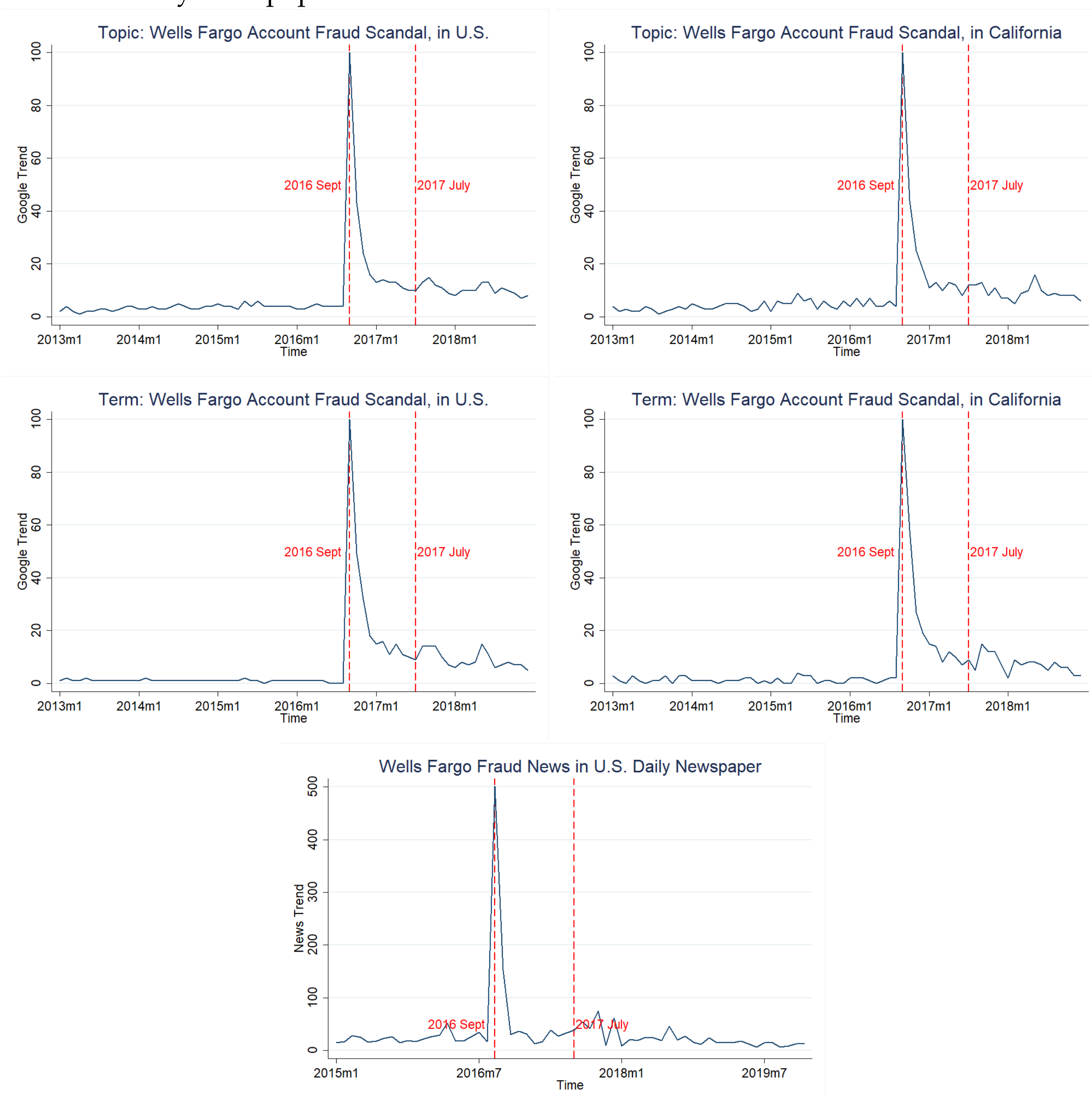

Figure 4: Exposure of Wells Fargo Scandal

This figure displays different county exposure to Wells Fargo Account Fraud Scandal measured by Wells Fargo deposits share in 2015. Deposit data is from Summary of Deposits.

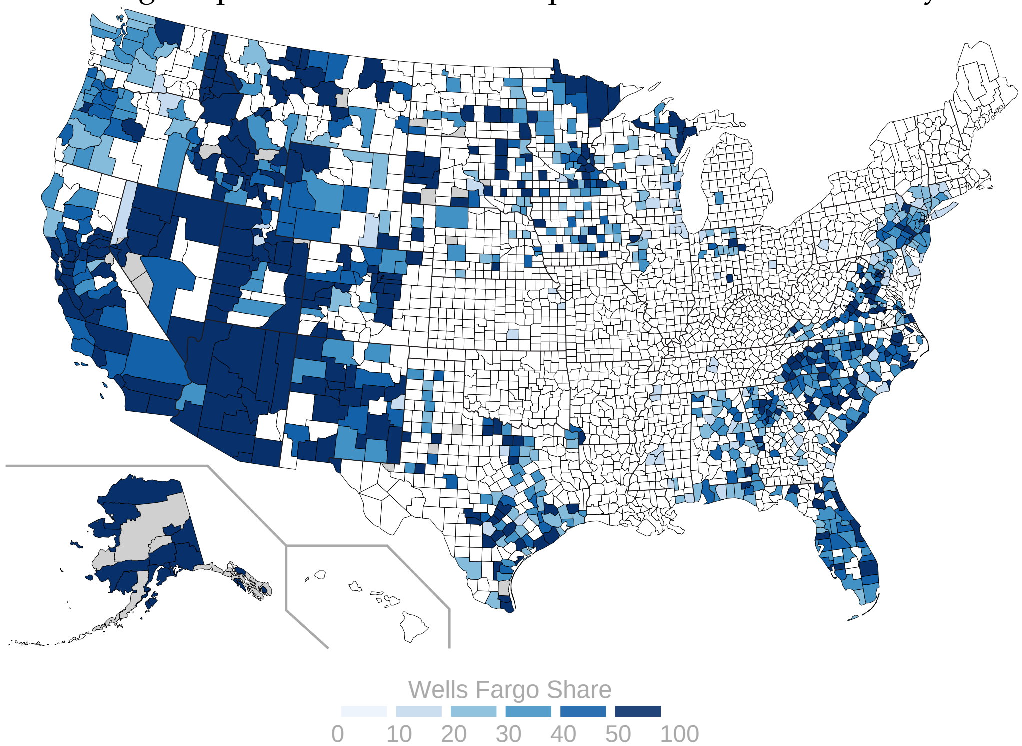

Figure 5: Google Search Intensity

This figure displays state level exposure of Wells Fargo Account Fraud Scandal measured by google search intensity of topic ”Wells Fargo account fraud scandal”.

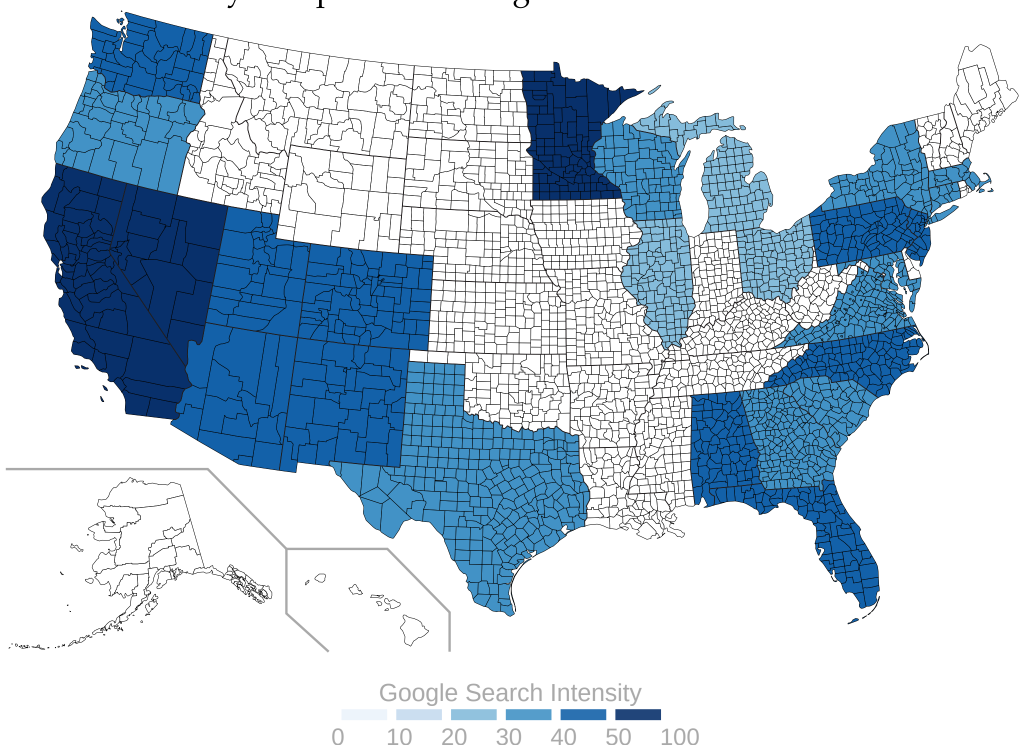

Figure 6: Political Affiliation

This figure displays county level share of votes for non-republican in 2016 presidential election.

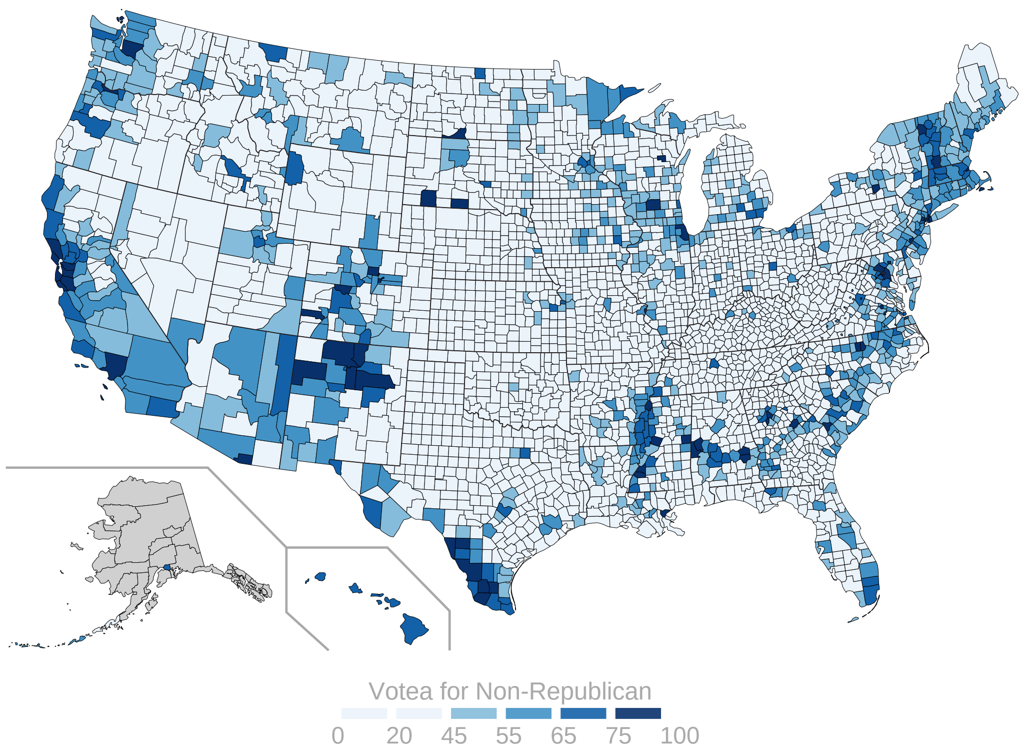

Figure 7: The effect of the revelation of bank misconduct on Trust in Banks

This figure reports the effects of 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.

$$y_{i,s,c,t} = \beta WFExposure_c \times \sum_{t=2015,t\neq2015}^{2018} Dummy_t + Control_{i,t} + \lambda_z + \sigma_t \times \eta_s + \varepsilon_{i,t}$$

The dependent variable is respondent's trust in banks, equaling to one if individual reported level of confidence in banks as "a great deal" or "a lot", zero if reported "very little" or "some". WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Dummy is dummy variable equaling to one at year t. The model is fully saturated by leaving out year 2015 dummy. The regression are run in subsamples, including Republican or Non-Republican respondents, Republican or Non-Republican respondents with high Trust in Media, Republican or Non-Republican respondents with low Trust in Media. 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.

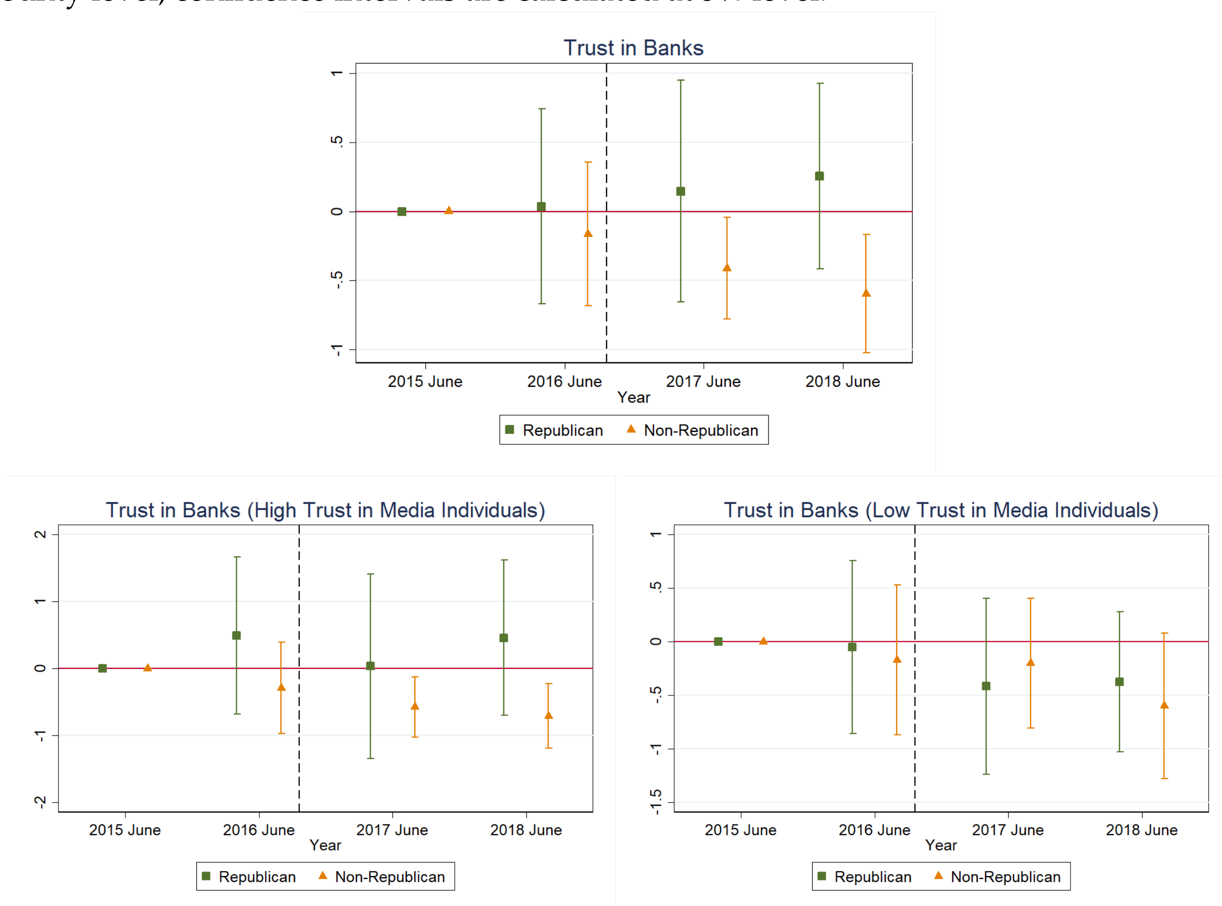

Figure 8: Dynamic effects of the revelation of bank misconduct on FinTech adoption

This figure reports the dynamic effects of the revelation of bank misconduct on mortgage loan origination. Coefficients are estimated from the follow 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 share of number of mortgage originated by FinTech lenders, for both origination and application. WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. NonRep is percentage of share voted for Non-Republican candidates in 2016 election. Post is Dummy is equaling to one after 2016. dummy variable equaling to one at year t. The model is fully saturated by leaving out year 2015 dummy. 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.

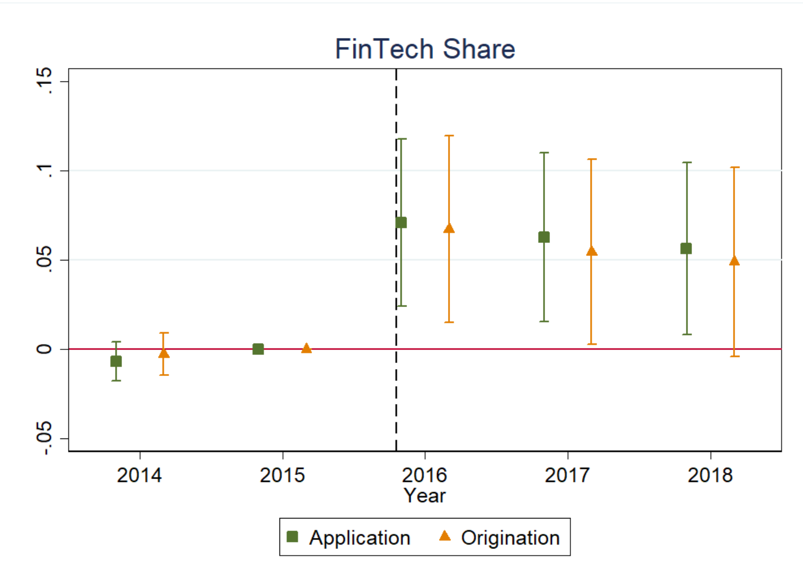

Table 1: Summary Statistics

Table A and table B presents counties with population larger than 65000.

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×Democrat	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

Table 1: Summary Statistics

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 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 bank misconduct on FinTech adoption

This table reports the effect of the revelation of bank misconduct on mortgage loan origination. Coefficients are estimated from the follow regression, using loan application 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 dummy variable equaling to 100 if the lender is FinTech. In column (1) (2) (4) (5), $Treated_c$ is the percentage points of Wells Fargo deposits in county c in 2015. In column (3) (6), $WFExposure_c$ is Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. $Post_t$ is dummy equaling to 1 after 2016. Column (1) (2) (3) only include originated loans and column (4) (5) (6) include all applications. Control variables are defined in the appendix. 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)	(5)	(6)
	FinTech	FinTech	FinTech	FinTech	FinTech	FinTech
WF Exposure× Post	0.013***	0.011***	0.006***	0.012***	0.010**	0.006***
	(3.5)	(2.7)	(2.7)	(3.3)	(2.6)	(2.6)
Population		0.002	0.001		0.003	0.002
		(1.0)	(0.9)		(1.6)	(1.5)
Median Household Income		0.000	0.000		-0.000	-0.000
		(1.3)	(1.0)		(-0.9)	(-1.3)
Unemployment Rate		-0.058**	-0.048*		-0.058**	-0.048*
		(-2.1)	(-1.8)		(-2.2)	(-1.9)
% with less than 35K income		-0.013	-0.016		-0.035**	-0.038**
		(-0.8)	(-1.0)		(-2.4)	(-2.6)
Top 4 Share		-2.360***	-2.375***		-2.520***	-2.517***
		(-3.8)	(-4.0)		(-4.2)	(-4.4)
Income	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-7.1)	(-6.9)	(-6.9)	(-5.8)	(-5.5)	(-5.5)
Loanamt	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-5.2)	(-4.9)	(-4.9)	(-4.7)	(-4.4)	(-4.4)
Type (Omitted Category = Conventional)						
FHA	2.754***	2.443***	2.443***	4.404***	4.040***	4.040***
	(16.4)	(14.4)	(14.4)	(22.6)	(19.7)	(19.7)
VA	0.137	0.077	0.076	1.493***	1.383***	1.383***
	(1.2)	(0.6)	(0.6)	(11.0)	(9.3)	(9.3)
FSA/RHS	-2.217***	-1.742***	-1.744***	-2.121***	-1.416***	-1.417***
	(-12.2)	(-8.3)	(-8.3)	(-13.7)	(-7.4)	(-7.4)
Home Improvement	-1.182***	-0.930***	-0.930***	-4.278***	-3.629***	-3.630***
	(-11.1)	(-7.5)	(-7.5)	(-30.5)	(-24.2)	(-24.2)
Refinance	7.201***	7.343***	7.343***	6.367***	6.750***	6.750***
	(41.7)	(37.2)	(37.2)	(46.8)	(43.7)	(43.7)
Purchaser (Omitted Category = Held)						
Fannie Mae	11.081***	11.257***	11.257***	7.470***	7.771***	7.771***
	(56.6)	(51.3)	(51.3)	(39.6)	(37.8)	(37.8)
Ginnie Mae	11.433***	11.144***	11.145***	5.975***	5.933***	5.934***
	(41.4)	(35.7)	(35.7)	(29.6)	(25.9)	(25.9)
Freddie Mac	9.194***	9.350***	9.351***	5.615***	5.896***	5.897***
	(31.4)	(28.2)	(28.2)	(18.9)	(17.8)	(17.8)
Farmer Mac	-0.344	-0.416	-0.410	-4.408***	-4.383***	-4.378***
	(-1.1)	(-1.1)	(-1.0)	(-16.0)	(-12.5)	(-12.5)
Private securitization	1.214***	1.535***	1.534***	-3.016***	-2.478***	-2.480***
	(3.8)	(4.6)	(4.6)	(-8.7)	(-6.8)	(-6.9)
Bank	2.441***	2.788***	2.788***	-1.781***	-1.232***	-1.233***
	(6.6)	(6.9)	(6.9)	(-4.6)	(-3.0)	(-3.0)
Insurance	0.701***	1.069***	1.070***	-3.851***	-3.269***	-3.269***
	(3.4)	(4.8)	(4.8)	(-18.2)	(-15.0)	(-15.0)
Affiliate	-2.610***	-2.381***	-2.382***	-6.352***	-6.007***	-6.008***
	(-15.5)	(-13.4)	(-13.4)	(-32.2)	(-28.5)	(-28.5)
Other	0.419**	0.810***	0.811***	-4.084***	-3.490***	-3.489***
	(2.2)	(3.8)	(3.9)	(-20.6)	(-16.6)	(-16.7)
Sex (Omitted Category = Male)						
Female	-0.750***	-0.834***	-0.834***	-0.664***	-0.802***	-0.802***
	(-22.5)	(-22.8)	(-22.8)	(-18.7)	(-21.1)	(-21.1)
Ethnicity (Omitted Category =)						
Hispanic	-2.709***	-2.756***	-2.756***	-2.364***	-2.442***	-2.442***
	(-14.0)	(-13.9)	(-13.9)	(-12.2)	(-12.2)	(-12.2)
Race (Omitted Category = White)						
Native American	0.424***	0.460***	0.460***	0.482***	0.462***	0.463***
	(3.3)	(3.1)	(3.2)	(4.1)	(3.4)	(3.4)
Asian	-2.236***	-2.264***	-2.264***	-2.533***	-2.542***	-2.542***
	(-12.8)	(-12.6)	(-12.6)	(-15.8)	(-15.3)	(-15.3)
Black	-1.357***	-1.43[illegible]	-1.431***	-1.177***	-1.489***	-1.489***
	(-13.8)	(-14.2)	(-14.2)	(-10.7)	(-14.2)	(-14.2)
Hawaiian	-1.161***	-1.168***	-1.168***	-1.255***	-1.294***	-1.294***
	(-8.0)	(-7.8)	(-7.7)	(-10.0)	(-9.9)	(-9.9)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	34179861	29985964	29985964	44856156	39029308	39029308

Table 3: The Dynamic effects of revelation of Well Fargo scandal on FinTech adoption

This figure reports the dynamic effects of the revelation of bank misconduct on mortgage loan origination. Coefficients are estimated from the follow regression, using county - year level data from 2014 to 2018.

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

The dependent variable is share of number of mortgage originated by FinTech lenders, for both origination and application. WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. NonRep is percentage of share voted for Non-Republican candidates in 2016 election. Post is Dummy is equaling to one after 2016. dummy variable equaling to one at year t. The model is fully saturated by leaving out year 2015 dummy. 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.

	Origination	Application
	(1)	(2)
	FinTech	FinTech
2014	-0.003	-0.007
	(0.463)	(-1.231)
2015	1	1
2016	0.067^{***}	0.071^{***}
	(2.536)	(2.961)
2017	0.054^{***}	0.063^{***}
	(2.059)	(2.601)
2018	0.049^{**}	0.057^{***}
	(1.816)	(2.30)

Table 4: The effect of the revelation of bank misconduct on lender choice

This table reports the effect of the revelation of bank misconduct on mortgage loan origination. Coefficients are estimated from the follow regression, using loan application 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 dummy variable equaling to 100, indicating lender type. WF Exposure is the percentage points of Wells Fargo deposits in county c in 2015. Post is dummy equaling to 1 after 2016. Control variables are defined in the appendix. 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.

	(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 Type (Omitted Category = Conventional)						
FHA	2.443***	-0.590***	-18.512***	-19.102***	16.659***	19.102***
	(14.4)	(-7.8)	(-38.4)	(-41.8)	(41.9)	(41.8)
VA	0.077	0.288***	-7.689***	-7.401***	7.325***	7.401***
	(0.6)	(2.9)	(-16.0)	(-16.9)	(17.4)	(16.9)
FSA/RHS	-1.742***	0.693***	-15.567***	-14.875***	16.617***	14.875***
	(-8.3)	(6.9)	(-26.2)	(-24.8)	(26.9)	(24.8)
Purpose (Omitted Category = Purchase)						
Home Improvement	-0.930***	1.737***	11.620***	13.356***	-12.426***	-13.356***
	(-7.5)	(6.5)	(39.0)	(33.6)	(-30.7)	(-33.6)
Refinance	7.343***	-0.400***	1.413***	1.013***	-8.356***	-1.013***
	(37.2)	(-3.0)	(6.6)	(4.1)	(-25.3)	(-4.1)
Purchaser (Omitted Category = Held)						
Fannie Mae	11.257***	2.995***	-47.739***	-44.743***	33.487***	44.743***
	(51.3)	(7.3)	(-105.3)	(-67.2)	(55.6)	(67.2)
Ginnie Mae	11.144***	-2.236***	-45.367***	-47.603***	36.459***	47.603***
	(35.7)	(-6.7)	(-78.5)	(-62.1)	(45.1)	(62.1)
Freddie Mac	9.350***	2.548***	-43.357***	-40.809***	31.459***	40.809***
	(28.2)	(5.8)	(-91.5)	(-60.0)	(49.2)	(60.0)
Farmer Mac	-0.416	-6.528***	-56.193***	-62.721***	63.137***	62.721***
	(-1.1)	(-14.4)	(-19.3)	(-21.7)	(22.2)	(21.7)
Private securitization	1.535***	-6.538***	-50.774***	-57.313***	55.777***	57.313***
	(4.6)	(-14.2)	(-43.7)	(-44.0)	(43.4)	(44.0)
Bank	2.788***	-6.141***	-50.271***	-56.412***	53.624***	56.412***
	(6.9)	(-15.1)	(-56.7)	(-50.7)	(46.3)	(50.7)
Insurance	1.069***	-5.883***	-48.886***	-54.769***	53.699***	54.769***
	(4.8)	(-15.8)	(-57.7)	(-50.7)	(52.7)	(50.7)
Affiliate	-2.381***	-6.409***	-28.583***	-34.992***	37.373***	34.992***
	(-13.4)	(-14.6)	(-13.2)	(-16.8)	(17.9)	(16.8)
Other	0.810***	-5.207***	-52.214***	-57.421***	56.611***	57.421***
	(3.8)	(-13.6)	(-60.7)	(-55.8)	(56.6)	(55.8)
Sex (Omitted Category = Male)						
Female	-0.834***	-0.258***	-0.039	-0.297***	1.131***	0.297***
	(-22.8)	(-7.3)	(-0.6)	(-5.1)	(17.4)	(5.1)
Ethnicity (Omitted Category =)						
Hispanic	-2.756***	0.594***	-0.559**	0.035	2.721***	-0.035
	(-13.9)	(5.0)	(-2.5)	(0.1)	(8.9)	(-0.1)
Race (Omitted Category = White)						
Native American	0.460***	0.355*	-0.206	0.149	-0.608*	-0.149
	(3.1)	(1.9)	(-0.6)	(0.4)	(-1.9)	(-0.4)
Asian	-2.264***	-0.145	0.771*	0.626	1.638***	-0.626
	(-12.6)	(-0.9)	(1.8)	(1.3)	(3.4)	(-1.3)
Black	-1.431***	0.323***	-1.081***	-0.758***	2.189***	0.758***
	(-14.2)	(3.5)	(-4.5)	(-2.9)	(8.7)	(2.9)
Hawaiian	-1.168***	-0.595***	0.750**	0.155	1.014***	-0.155
	(-7.8)	(-3.4)	(2.4)	(0.6)	(3.2)	(-0.6)
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 5: The effect of revelation of Well Fargo scandal on trust in banks

This table reports effects of Wells Fargo account fraud 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.

$$y_{i,s,c,t} = \beta WFExposure_c \times Post_t + Control_{i,t} + \lambda_z + \sigma_t \times \eta_s + \varepsilon_{i,t}$$

The dependent variable is respondent's trust in banks, equaling to one if individual reported level of confidence in banks as "a great deal" or "a lot", zero if reported "very little" or "some". WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is dummy equaling to 1 after 2016 Sept. Control variables are defined in the appendix. Constant term is included and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics in parentheses.

	Trust in Banks			Trust in Big Business		
	(1)	(2)	(3)	(4)	(5)	(6)
WF Exposure× Post	-0.279**	-0.277**	-0.272**	-0.002	-0.046	-0.012
	(-2.1)	(-2.1)	(-2.2)	(-0.0)	(-0.4)	(-0.1)
Republican		6.517***	8.079***		15.293***	19.995***
		(3.9)	(4.6)		(9.6)	(12.0)
Age		-0.060	-0.120**		0.071*	0.044
		(-1.2)	(-2.5)		(1.7)	(1.1)
Male		2.932*	2.749*		-5.185***	-6.137***
		(1.9)	(1.8)		(-3.6)	(-4.0)
College Education		-3.014	-1.284		-3.945**	-3.394**
		(-1.6)	(-0.7)		(-2.4)	(-2.0)
High Income		2.477	0.915		3.668**	3.682**
		(1.5)	(0.6)		(2.5)	(2.4)
White		-4.443	-2.030		-4.733	-4.643
		(-1.4)	(-0.6)		(-1.5)	(-1.4)
Black		-2.044	-0.460		0.043	0.602
		(-0.5)	(-0.1)		(0.0)	(0.1)
Hispanic		-6.579	-3.603		-3.132	-2.824
		(-1.6)	(-0.9)		(-0.8)	(-0.7)
Protestant		4.083**	3.995**		0.256	0.083
		(2.6)	(2.6)		(0.2)	(0.1)
Jewish		0.413	-0.568		-2.591	-3.440
		(0.1)	(-0.1)		(-0.6)	(-0.8)
Trust in Media			0.390***			0.254***
			(11.3)			(7.0)
Trust in Big Business			0.322***			
			(15.0)			
% with less than 35K income			-0.992			-1.027*
			(-1.6)			(-1.7)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	4255	4074	3693	4237	4063	3715
Adjusted R^2	0.003	0.062	0.138	0.004	0.061	0.063

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

This table reports heterogeneous effects of Wells Fargo account fraud 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.

$$y_{i,s,c,t} = \beta WFExposure_c \times Post_t + Control_{i,t} + \lambda_z + \sigma_t \times \eta_s + \varepsilon_{i,t}$$

The dependent variable is respondent's trust in banks, equaling to 100 if individual reported level of confidence in banks as "a great deal" or "a lot", zero if reported "very little" or "some" or "none". WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is dummy equaling to 1 after 2016 Sept. Column (1) - (5) report results only including individuals identified as Republican or Lean Republican. Column (6) - (10) report results only including individuals identified as Independent, Lean Democrat or Democrat. Control variables are defined in the appendix. In column (3) (4) (5) and (8) (9) (10), sample are divided into individuals with High Trust in Media, Median Trust in Media, and Low Trust in Media, based on their reported trust level in TV and Newspaper. 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									
	Non-Republican					Republican				
			Trust in Media					Trust in Media		
			High	Median	Low			High	Median	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WF Exposure× Post	-0.441***	-0.459***	-1.149**	-0.629***	-0.386	0.016	0.195	-3.158**	-0.203	-0.366
	(-3.1)	(-3.3)	(-2.4)	(-2.7)	(-1.3)	(0.1)	(0.7)	(-2.3)	(-0.4)	(-1.1)
Age		-0.016	-0.448**	0.096	-0.116		-0.075	0.701*	-0.115	0.039
		(-0.2)	(-2.6)	(0.9)	(-1.0)		(-0.9)	(1.8)	(-0.5)	(0.4)
Male		1.429	1.468	-3.945	8.653**		0.819	-34.893	-7.505	1.109
		(0.7)	(0.3)	(-0.9)	(2.2)		(0.3)	(-1.7)	(-0.9)	(0.3)
College Education		-2.767	-23.225***	5.377	6.356*		-3.126	-7.153	12.305	-3.591
		(-1.1)	(-2.9)	(1.0)	(1.7)		(-0.9)	(-0.4)	(1.3)	(-0.7)
High Income		-1.312	5.533	-3.322	-2.509		6.461**	-36.292	9.727	8.867**
		(-0.6)	(0.8)	(-0.8)	(-0.6)		(2.0)	(-1.5)	(1.0)	(2.3)
White		-3.896	3.430	-2.302	-10.893		-9.098	-19.789	0.822	-3.297
		(-0.9)	(0.3)	(-0.3)	(-1.2)		(-1.5)	(-0.6)	(0.1)	(-0.3)
Black		0.137	-17.088	4.712	-5.509		-11.680	-42.434	18.887	-8.003
		(0.0)	(-1.2)	(0.6)	(-0.5)		(-1.5)	(-0.9)	(1.2)	(-0.7)
Hispanic		-7.870	-7.681	-6.475	-15.652*		-14.706	-68.580*	-38.363*	4.290
		(-1.6)	(-0.5)	(-0.7)	(-1.7)		(-1.5)	(-1.8)	(-1.7)	(0.4)
Protestant		5.510**	11.772	0.188	9.299**		3.590	30.557	-1.041	-0.014
		(2.3)	(1.5)	(0.0)	(2.0)		(1.1)	(1.7)	(-0.1)	(-0.0)
Jewish		-5.069	-4.942	-10.996	-3.227		14.422	-55.671**	26.747	-3.406
		(-1.0)	(-0.4)	(-1.5)	(-0.2)		(1.2)	(-2.2)	(1.2)	(-0.2)
% with less than 35K income		-1.618*	-6.784*	-0.902	-0.911		-1.365	-6.449	1.947	-1.499
		(-1.7)	(-1.9)	(-0.5)	(-0.5)		(-1.1)	(-0.9)	(0.7)	(-0.8)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2170	2030	370	720	542	1664	1505	67	286	824
Adjusted R^2	0.014	0.014	0.018	-0.023	-0.026	-0.003	-0.018	0.175	-0.005	-0.028

Table 7: The effect of the revelation of bank misconduct on FinTech lenders

This table reports the effect of the revelation of bank misconduct on mortgage loan origination. Coefficients are estimated from the follow 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 share of number of mortgage originated by FinTech lenders, for both origination and application. WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is dummy equaling to 1 after 2016. NonRep is percentage of share voted for Non-Republican candidates in 2016 presidential election. In column (2) (3) (5) (6), sample are divided into counties with high and low Non-Republican voting shares. Control variables are defined in the appendix. 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)	(2)	(3)	(4)	(5)	(6)
	FinTech	FinTech	FinTech	FinTech	FinTech	FinTech
WF Exposure× Post× Dem	0.058**			0.067***		
	(2.2)			(2.8)		
Treated× 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)
Dem× 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: The effect of the revelation of bank misconduct on lenders' credit supply

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

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

The dependent variable is percentage of mortgage denied by different lender. WF Exposure is the percentage points of Wells Fargo deposits in county c in 2015. Post is dummy equaling to 1 after 2016. Control variables are defined in the appendix. 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.

	(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)
Population	-0.012***	0.005	-0.016***	-0.016***	0.017***	0.026***	0.031***
	(-3.7)	(0.8)	(-3.4)	(-3.5)	(3.2)	(5.1)	(5.1)
% Female	0.054	-0.401	-0.035	-0.044	0.111	-0.138	-0.185
	(0.7)	(-1.4)	(-0.3)	(-0.4)	(0.6)	(-1.2)	(-1.3)
% African American	0.032	0.568***	-0.068	-0.125	-0.252*	-0.038	0.025
	(0.6)	(2.9)	(-0.8)	(-1.6)	(-1.9)	(-0.5)	(0.3)
% Hispanic	-0.281**	-0.311	-1.050***	-1.028***	0.508**	0.043	0.035
	(-2.5)	(-0.8)	(-5.8)	(-5.5)	(2.0)	(0.3)	(0.2)
% over 21	-0.063	0.068	-0.143*	-0.127	-0.070	0.040	0.102
	(-1.0)	(0.3)	(-1.9)	(-1.6)	(-0.5)	(0.5)	(1.0)
% over 65	-0.224**	0.345	-0.226	-0.290**	-0.414*	-0.175	-0.145
	(-2.1)	(1.0)	(-1.6)	(-2.0)	(-1.7)	(-1.1)	(-0.7)
% with less than 12th grade education	-0.061**	0.030	-0.055	-0.072**	-0.062	0.020	0.034
	(-2.4)	(0.3)	(-1.6)	(-2.1)	(-0.9)	(0.5)	(0.8)
% with bachelor degree or higher	-0.041**	-0.011	-0.058**	-0.065**	-0.037	0.013	0.029
	(-2.1)	(-0.1)	(-2.0)	(-2.4)	(-0.8)	(0.5)	(0.8)
% living in the same house last year	-0.024	0.024	-0.022	-0.023	0.076*	0.043*	0.038
	(-1.5)	(0.4)	(-1.0)	(-1.1)	(1.9)	(1.7)	(1.3)
Median Household Income	-0.000***	0.000**	-0.000***	-0.000***	0.000***	0.000***	0.000***
	(-10.8)	(2.5)	(-9.0)	(-9.6)	(2.6)	(6.8)	(6.7)
Unemployment Rate	-0.130***	0.054	-0.092**	-0.103***	0.130**	0.151***	0.177***
	(-4.9)	(0.5)	(-2.3)	(-2.7)	(2.0)	(4.0)	(3.8)
% with less than 35K income	-0.154***	0.091	-0.133***	-0.135***	0.124***	0.150***	0.173***
	(-8.0)	(1.4)	(-5.5)	(-5.7)	(2.9)	(5.7)	(5.3)
Top 4 Share	2.170***	1.322	3.361***	3.783***	0.386	2.849**	4.661***
	(2.8)	(0.5)	(3.5)	(3.9)	(0.2)	(2.4)	(3.2)
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

Table 9: Deposits

This table reports the effect of the revelation of bank misconduct on deposits. Coefficients are estimated from the follow regression, using county - year level data from 2014 to 2018.

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

The dependent variable is per capita and log value of deposits in county c at time t. Treated is the percentage of Wells Fargo deposits in county c in 2015. Post is dummy equaling to 1 after 2016. Less Trust in Tech are counties with average trust in technology less than 0.66 from Pew Research Center Poll. Control variables are defined in the appendix. 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.

	Log Value Deposits			Deposits Per Capita		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Wells Fargo	Non-Wells Fargo	Total	Wells Fargo	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)
Population	0.001***	0.002	0.001***	0.012	-0.027	0.040*
	(2.7)	(1.5)	(2.8)	(0.4)	(-1.1)	(1.7)
% Female	0.006**	0.002	0.006**	-0.441	-0.543	0.102
	(2.3)	(0.5)	(2.1)	(-0.8)	(-1.0)	(1.0)
% African American	0.001	0.010	-0.001	0.747	1.014	-0.267*
	(0.3)	(1.1)	(-0.5)	(0.8)	(1.0)	(-1.8)
% Hispanic	-0.008*	-0.011	-0.010**	-2.345	-1.909	-0.436
	(-1.7)	(-0.6)	(-2.1)	(-1.4)	(-1.0)	(-1.0)
% over 21	0.003*	-0.005	0.003*	0.090	0.024	0.066
	(1.8)	(-0.9)	(1.7)	(0.6)	(0.4)	(0.5)
% over 65	0.003	-0.016	0.004	-1.003	-1.747	0.745**
	(0.5)	(-1.1)	(0.6)	(-0.6)	(-1.0)	(2.0)
% with less than 12th grade education	0.002*	0.006	0.002*	-0.012	-0.107	0.094*
	(1.7)	(0.9)	(1.9)	(-0.1)	(-1.0)	(1.7)
% with bachelor degree or higher	0.001*	0.001	0.002**	0.128	0.089	0.039
	(1.9)	(0.4)	(2.2)	(1.5)	(0.9)	(0.7)
% living in the same house last year	0.000	-0.002	0.000	-0.022	-0.033	0.011
	(0.3)	(-1.4)	(0.7)	(-0.6)	(-1.1)	(0.3)
Median Household Income	0.000***	0.000**	0.000***	-0.000	-0.000	0.000**
	(4.8)	(2.0)	(4.4)	(-0.1)	(-0.9)	(2.4)
Unemployment Rate	-0.000	-0.003	0.000	0.121	0.089	0.032
	(-0.1)	(-0.7)	(0.0)	(1.1)	(0.9)	(0.7)
% with less than 35K income	0.003***	-0.001	0.003***	0.086	-0.068	0.154**
	(3.3)	(-0.3)	(3.1)	(0.9)	(-0.8)	(2.5)
Top 4 Share	0.001	-0.013	0.003	0.688	2.514	-1.826
	(0.0)	(-0.1)	(0.1)	(0.2)	(0.9)	(-0.7)
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: The effect of the revelation of bank misconduct 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 follow 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 variables are percentage of mortgage denied by different lender and per capita and log value of deposits in county c at time t. WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is dummy equaling to 1 after 2016. NonRep is percentage of share voted for Non-Republican candidates in 2016 presidential election. In column (2) (3) (5) (6), sample are divided into counties with high and low Non-Republican voting shares. Control variables are defined in the appendix. 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.

	(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× Dem	-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)
Treated× 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)
Dem× 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	
County FE	Y	Y	Y	Y	Y	Y	
Year FE	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

	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× Dem	-0.005**	-0.015*	-0.003	-0.841	-0.700	-0.141
	(-2.0)	(-1.8)	(-1.4)	(-1.5)	(-1.1)	(-0.5)
Treated× 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)
Dem× 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