Fintech, Bank Branch Closings,
and Mortgage Markets *

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Job Market Paper

October 6, 2021

Abstract

This paper studies whether bank branch closures affect fintech mortgage lending in the U.S. during the 1999-2016 period. To generate plausibly exogenous variation in the incidence of closings, I use an instrument based on within-county, tract-level variation in exposure to post-merger branch consolidation. I find that branch closures lead to a persistent increase in fintech lending. Fintech mortgages grow by a total of 8% in the 9 years that follow a closing, while bank mortgage lending falls by 44%, off an annual baseline of 340 mortgages. Fintech lending grows faster in areas that are richer, and have relatively smaller populations of women, seniors and minorities.

Keywords: *Fintech, credit markets, branch closings, digital banking*
JEL Classification: D14, G21, G23, G51

1 Introduction

Since the onset of the Great Recession in 2007, the US consumer lending market has gone through two major disruptions. First, a persistent wave of bank branch closings which, according to the Federal Deposit Insurance Corporation (FDIC), represents a 12% overall decline in bank branches from the pre-recession maximum, and is expected to continue in the coming years[1]. And second, the rise and consolidation of a new type of lender: fintech —a lender characterised by its intensive use of technology to provide financial services. The footprint that these new lenders have managed to achieve in relatively little time is remarkable. Fintech share of the mortgage market has exploded in the last two decades. From a zero market share in the early 2000's, to nowadays representing more than 12% of the overall US mortgage market[2].

Given the significance of the two disruptions for credit markets, the literature has scrutinized their effects and has unveiled important consequences. For instance, bank branch closings have been linked to an increase in the interest paid by borrowers and firms (Fuster et al. (2019); Bonfim et al. (2020)), to a reduction of credit supply (Nguyen (2019)), to the creation of "banking deserts"[3] (Morgan et al. (2016)), and to specially severe contractions of credit for low income and minority groups (Nguyen (2019)). While research on the effects of fintech, have shown that fintech both facilitates refinancing and improves mortgage supply after demand shocks (Fuster et al. (2019)). That fintech companies, by relying on algorithmic techniques like data mining and big data use fintech companies can deny historically disadvantaged and vulnerable groups full participation in society (Barocas and Selbst (2016)). And, finally that despite fintech growth is partly based on this intensive use of technology the most contributing factor to its growth is regulation arbitrage Buchak et al. (2018) (basing its growth in the lower regulation that fintech has relative to banks) which could lead to financial instability.

Despite these evidence, there is still no research on the interplay between these two disruptions. This is precisely what I do in this paper. To my knowledge, this is the first study about the effect of bank branch closings on fintech adoption and its consequences for credit markets. I study their effect in the US mortgage market, a $11.05 trillion market that is of vital interest for the lives of most American citizens, and that is key, for the vitality, profitability, and stability of the overall US financial system as the 2007-2009 financial crisis portrayed.

As both banks and fintech lenders are competitors in the mortgage market, the first

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[1]Amounts to a total of 10,631 for the 2008-2020.
[2]According to the 2015 Home Mortgage Disclosure Act data.
[3]Areas with no bank branch within 10 miles.

question that I explore is whether banks, by deserting certain areas with branch closings are fostering the growth of fintech. To test this, I first estimate the causal effect of branch closings on fintech mortgage originations. I then proceed to test whether the decision of banks to downsize their branch network is affecting the overall supply of credit offered by banks in affected areas. To test this, I estimate the causal effect of branch closings on bank mortgage supply. Finally, I test whether the effects of branch closings are specially severe for certain population groups. I do this by measuring both the effects of branch closings on fintech and banks for a set of special interest population subgroups.

To study the effect of branch closings on local mortgage fintech adoption I use a quasi-experimental research design based on Home Mortgage Disclosure Act (HMDA) data, which is the most comprehensive source of publicly available information on the U.S. mortgage market[4]. Studying the effect of branch closings on local mortgage markets poses an empirical challenge. Banks tend to close branches in areas where current or expected profitability is low, and since profitability is also related to tract characteristics (U.S. Census tracts are small, relatively permanent statistical subdivisions of a county) that also affect mortgage credit, a simple study comparing areas in which a branch close and those in which there is no closing will produce a biased estimate of the effects of branch closings. To overcome this problem I use an instrument based on within-county, tract-level variation in exposure to post-merger branch consolidation as in Nguyen (2019).

Figure 1 illustrates this identification strategy for a sample merger and a sample county. This framework compares the pre-merger and post-merger level of lending in exposed tracts (those that had branches from both merging banks prior to the merger) relative to a set of control tracts located in the same county and with branches belonging to at least two large non-merging banks. The identifying assumption is that the decision to merge is exogenous to tract economic characteristics that also determine credit. To warrant this, I only include in my sample mergers between large banks. That is, banks that pre-merger, had at least $50 bn in assets, which puts them roughly at the 1% asset size distribution of US banks. The business size of exposed tracts represents such a minimal share of the participating banks profits, that the plausibility of the decision to merge being linked to these area characteristics is extremely low. The ultimate goal of this empirical framework is to compare tracts that, ex ante, were equally likely to have been exposed to a large bank merger. To evaluate the effects of closings in fintech lenders, I then classify all institutions that report HMDA data in into three types: banks, shadow banks, or fintechs using established methods in the literature (Buchak et al. (2018); Fuster et al. (2019); Jagtiani et al. (2019)).

[Figure 1 about here.]

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[4]Capturing 90 percent of lending activity measured by loan volume.

My main results are as follows: first, I show that branch closings increase local mortgage fintech adoption persistently. Fintech mortgages on aggregate increase by 8% in the nine years that follow a closing, out of an annual baseline of 340 bank mortgages[5]. All in all, these effects suggest that the use of technology by fintech lenders may allow them to better cater to the needs of the "unbranched" borrowers, as my comparisons are between constant regulation areas. Second, I show that branch closings persistently reduce the mortgage supply offered by banks. The effect of the average closing in the nine years that follows, produces a decrease of 42% in the number of bank mortgages with respect to the annual baseline. This finding highlights the important role of branches, which even in the fintech era, reduce information asymmetries that represent frictions for the correct functioning of the mortgage market. Finally, I provide evidence that suggests that the effects of branch closings significantly differs across population groups. After closings, poor, low minority and older population areas suffer a steeper reduction of bank mortgages than the average area in the study. However, rich, low minority, low female and younger populated areas are driving the increase of fintech mortgages. These findings suggest that the change in the lender mix has important consequences for the type of borrower that is able to get a mortgage post-closing and, even more importantly, for those that no longer can get one. This further raises concerns about the role of financial technologies, such as algorithm based screening and big data use for loan approval decisions in the financial sector and its repercussions for the financial inclusion of vulnerable groups of the population.

This paper contributes to three strands of the banking literature. First, I provide novel evidence on the effects of branch closings in credit markets. As the main contribution of the paper I show that previous tests on the topic that showed that there was no overall effect of closings in the mortgage supply, but only a reduction of credit for small business loans (Nguyen (2019)) and in pricing to firms (Bonfim et al. (2020)), were obscuring a crucial change. Here I show that closings cause a significant change in the lender mix that provides the mortgage supply. More precisely, I show that closings cause a substitution effect in the lenders of the mortgage market. This change occurs between banks, who reduce their mortgage supply, to fintech, who increase it. This finding is supporting evidence of the important role of bank branches even in this fintech era, characterized by the intensive use of technology and new channels to reach customers. In this paper I show that the branch role of facilitating bank-branch-borrower relationships and the transmission of soft information, is both important for firm credit outcomes, but also for household ones despite the presence of new technological advancements in the mortgage market.

Second, I contribute in explaining the elements that explain the rapid growth of fintech in credit markets. In the more positive light about these elements for growth, one view suggests

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[5]I use bank mortages as baseline since there are no fintech mortages before closings.

that new technology and the improved methods that it allows, is the main source of fintech growth. According to this view, the use of these new technologies is what is allowing fintech lenders to produce better services or to lend more cheaply to borrowers. For instance, Fuster et al. (2019) find that fintech lenders reduce frictions in the mortgage origination process, such as capacity constraints, slow processing times, and lower than optimal refinancing, while Buchak et al. (2018) show that fintech makes use of new technology to provide credit and attribute part of their growth to this use. Yet, another view is that fintech lenders are engaging in regulation arbitrage. That is, that fintech lenders are benefiting from their lower regulation relative to banks to capture part of their market share in credit markets. Buchak et al. (2018) bring additional evidence to support this view. The authors show that, indeed, fintech lenders are filling the gap left by banks, but that they have done so in segments where regulatory burden has risen substantially for banks, and relying almost exclusively on explicit and implicit government guarantees. Additionally, de Roure et al. (2021) show that stricter capital requirements fostered credit reallocation from banks to peer-to-peer fintech lending providers in the German consumer credit market after 2010 while Irani et al. (2020) show a similar effect for the U.S. corporate loan market between banks and non-banks. In this paper I provide evidence in support of the former view. By making comparisons between areas with the same regulation, and showing that after a branch closing, fintech lenders, and not other banks, are the ones that capture the "deserted" borrowers, my findings suggest that fintech lenders, either provide better products or offer cheaper mortgages, and do not only base their growth in regulation arbitrage.

Third, my analysis also contributes to the literature on the effects of fintech and bank branch closings on financial inclusion —financial inclusion implies that individuals and businesses have access to useful and affordable financial products and services that meet their needs delivered in a responsible and sustainable way[6]. The literature on the effects of closings for credit markets paints a negative view about its effects. For instance, Nguyen (2019) shows that bank branch closings disproportionately affect information-intensive borrowers, such as minorities and low income individuals, by reducing their access to credit. Morgan et al. (2016) shows that, after branch closings, since competitors do not fully replace incumbent "deserters" lending quota, credit is rationed in certain areas due to the creation of banking deserts which is more likely in low income areas —banking desert is defined as a relatively homogeneous area or neighborhood containing about 4,000 people with no branches within ten miles of its center. Regarding the effects of fintech, there are some findings that paint a more positive view about the role of fintech in facilitating financial inclusion. For instance, Bartlett et al. (2021), show that fintech lenders reduced disparities in the interest rate charged and do not incur in discrimination in mortgage application rejection for Latinx/African-Americans

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[6]Source: The World Bank.

compared to risk-equivalent borrowers. Yet, there is also a more pessimistic view about the effects of fintech for financial inclusion. Work by Barocas and Selbst (2016) uncovers the negative effects of algorithm decision-making for the financial inclusion of large segments of the US population. In the same light, Buchak et al. (2018) show that fintech lenders are less likely to serve less creditworthy FHA borrowers and higher unemployment geographies, or Bartlett et al. (2021) who show that fintech providers, despite reducing discrimination in pricing relative to traditional lenders for Latinx/African-Americans, still incur in discrimination in the interest rate charged to these customers that is not justified by their creditworthiness. Finally, Fuster et al. (2021) recently test the role of machine learning models in financial inclusion outcomes by predicting default in mortgages using traditional and machine learning models and find that Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning as machine learning increases disparity in rates between and within groups. In this paper, I show that the effects of closings indeed lead to bank credit rationing for information-intensive borrowers, such as minorities or poor individuals. Additionally I show that, although fintech partly fills the gap left by banks, it does so targeting richer, non-minority, younger, and male individuals, leaving other groups suffering the brunt of the decrease in credit.

The rest of the paper is organized as follows. Section 2 details data sources. Section 3 explains the lender classification methodology. Section 4 discusses the details of the empirical strategy used to identify the causal effect of interest. Section 5 analyzes the effect of branch closings on consumer lending markets. Section 6 concludes.

2   Data

All sources of data of the paper are at the census tract level. Census tracts are defined by the US Census Bureau as small, relatively permanent statistical subdivisions of a county designed to contain about 4,000 inhabitants[7], therefore, their size varies depending on their population density. After each census, the borders of some tracts are slightly updated[8]. In this paper I use 2000 census borders[9].

To analyze the impact of branch closings on local lending I obtain local mortgage lending data from the Home Mortgage Disclosure Act (HMDA) datasets published by the Federal

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[7]With a minimum of 1,200 inhabitants and a maximum of 8,000.

[8]Census tracts are split, merged or untouched, depending on population change, and small boundary corrections are sometimes allowed as well.

[9]For variables reported using other US census borders (1990 or 2010 census) I use a set of relationship files provided by the US census that show how the different census geographies relate to each other and allow to merge geographic entities over time.

Financial Institutions Examination Council (FFIEC). I use data for the 1999-2016 period[10]. HMDA data is the most comprehensive source of publicly available information on the U.S. mortgage market. The HMDA was enacted by Congress in 1975 and was implemented by the Federal Reserve Board. The Board requires lending institutions to report public loan data using a remarkably stable reporting criteria[11]. HMDA data are at the loan application level, and include information about the census tract in which the borrower is located[12], the amount of the application, whether the mortgage has been approved or denied, reason for denial (if denied), the name of the chartering agency of the institution, the purpose of the mortgage (i.e., home purchase/improvement/refinancing) and applicant characteristics such as gender, race or income. Crucially, HMDA data is based on the location of the borrower and not on the location of the lender. This allows me to estimate the impact of a branch closing on total mortgage supply to borrowers located in the same tract. I keep only mortgages classified by HMDA regulation as conventional, therefore, I drop mortgages originated by the Federal Housing Administration, the Veterans Administration and by the Farm Service or Rural Housing Service. I aggregate the remaining mortgages and create a yearly census tract-level measure of mortgage originations which I winsorize at the 1 percent level.

To construct the exposure instrument I first obtain the annual listing of all bank branches belonging to FDIC-insured institutions provided by the FDIC Summary of Deposits (SOD). The SOD is the annual survey of branch office deposits as of June 30 for all FDIC-insured institutions, including insured U.S. branches of foreign banks. All institutions with branch offices are required to submit the survey, only institutions with only a main office are exempt. Apart from the branch deposits information, the SOD contains data of the address of the branch, the GPS coordinates of the location of the branch (only from 2008 onwards), and information related to the institution that owns the branch. To locate bank branches for which the GPS coordinates are available in the SOD I use GIS software. For branches which GPS coordinates are not available I use a combination of Google Maps Geocoding API (to

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[10]The rest of data sources are for the same 1999-2016 period and at the census tract level unless I specify that it is not.

[11]According to the 2021 reporting criteria published by the FFIEC under HMDA banks, savings associations, or credit unions that: have at least $48 million in assets, have a home or branch office located in a metropolitan statistical area, originated at least one home purchase loan or refinancing of a home purchase loan, are federally insured or federally regulated or are insured, guaranteed or supplemented by a Federal agency or intended for sale to the Federal National Mortgage Association or the Federal Home Loan Mortgage Corporation, and meet or exceed either the closed-end mortgage loan-volume threshold or the open-end line of credit loan-volume threshold (effective January 1, 2018 through December 31, 2021, an institution that originated at least 25 closed-end mortgage loans, or originated at least 500 open-end lines of credit or exceeds the loan volume threshold) in each of the two preceding calendar years. Additionally, for-profit mortgage-lending institutions other than a banks, savings associations, or credit unions are subject to HMDA regulation if the institution had a home or branch office in a metropolitan statistical area and meets or exceeds either the previously mentioned closed-end mortgage or credit loan-volume threshold in each of the two preceding calendar years.

[12]Not based in the location of the lending financial institution.

find the GPS coordinates of a branch using its address information) and GIS software to locate its census tract. The percentage of non-located branches in the full SOD data for the 1999-2016 period is 0.7%. The percentage of unmapped observations in 1999 is 1.7% and declines to 0.03% in 2016.

To complete the construction of the exposure instrument I obtain data on bank branch closings and merger activity from FDIC's API. To locate the branch closings I use the same method as per the bank branches location. The percentage of non-located branch closings for the period of interest is 2.4%. The percentage of unmapped observations in 1999 is 5.9% and declines to 0.07% in 2016. To obtain bank mergers approved by regulators in the period of interest I download from FDIC's API all mergers with effective dates of inclusion in the 1999-2020 period[13]. I obtain federal approval dates by searching either for the corresponding order of approval documents released by the FED, a press release by participants in the merger, or for other regulators press release notes. I gather merger announcement dates by searching the announcement news or press releases in FACTIVA[14] database. Information relative to merger participants asset size is obtained from FDIC's statistics on depository institutions financial data report of the fourth quarter.

Finally, I gather tract-level demographic characteristics from the 2000 US census. The rest of data sources are for the 1999-2016 period.

3   Lender Classification

In this paper I classify all institutions that report HMDA data in the 1999-2016 period in three types: banks, shadow banks, or fintechs. To gather the list of institutions I first collect the annual HMDA Reporter Panels (RP) for the period of interest. The RP, includes information that identifies each institution (i.e., name, location...) and a variable that codes each type of lending institution[15]. Second, following Buchak et al. (2018) institution classification methodology, I classify as banks all depository institutions, and as shadow banks the rest of institutions[16].

Finally, to distinguish between shadow banks and fintechs I follow Jagtiani et al. (2019) classification, which is a mix of the fintech classifications by Buchak et al. (2018) and Fuster et al. (2019) plus two more recent lenders. I consider a shadow bank as fintech if it is classified

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[13]Since approval dates are always later than the effective dates, I look for the period 1999-2020

[14]Global news database of more than 33,000 sources owned by Dow Jones & Company.

[15]As either a: Bank, Saving Institution, Credit Union, Mortgage Banking Subsidiary (MBS) of Commercial Bank, MBS of Bank Holding Company or Service Corporation, Department of Housing and Urban Development, Private Mortgage Institution Corporation, or Affiliate

[16]Therefore Banks, Saving Institutions, Credit Unions and Mortgage Banking Subsidiaries of Commercial Banks or Bank Holding Companies or Services Corporations are classified in the paper as banks.

as such by any of the three papers. Buchak et al. (2018) and Fuster et al. (2019) consider an institution as fintech if it allows for mortgage preapproval or full approval without the borrower having to communicate directly with a loan officer or a broker. Additionally I classify as fintechs two institutions that started reporting HMDA data in 2016 which are classified as fintech by Jagtiani et al. (2019), but were not classified as such by Buchak et al. (2018), Fuster et al. (2019)[17], based on their growing volume and media recognition as best online mortgage providers. The list of included institutions is the following: AmeriSave Mortgage, Better Mortgage, CashCall Inc., Everett Financial, Guaranteed Rate, loanDepot, Movement Mortgage, SoFi, and Quicken. A summary of this classification method is displayed in figure 2.

[Table 1 about here.]

4   Empirical Strategy

Empirical challenge   The relationship of interest is the effect of branch closings on mortgage supply of the different lender types. Estimating this empirical relationship poses an empirical challenge: factors related to the incidence of branch closings that are also related to local economic characteristics that can correlate with mortgage lending. For example, branch closings tend to occur in bank low profitability areas and these areas generally have experienced credit demand shocks, which are also related to the local level of lending.

Instrument   As a solution for this empirical challenge I use as an instrument for branch closings the exposure to post-bank-merger consolidation, following Nguyen (2019) who pioneered this approach. Specifically, I exploit the plausible exogenous variation in the incidence of branch closings that follows a bank merger, as these post-merger closings in areas in which the merging branch networks overlap tend to be the result of network optimization and not of the day to day operations. Precisely because these closings are the result of the decision of the buyer banks to trim branches in areas in which the prior independent networks overlap. This both, increases the probability of branch closings, and decreases the likelihood that the decision to close a branch is based on local economic characteristics.

The identifying assumption is that tract-level exposure to bank mergers is as good as randomly assigned. Or stated differently, that the decision of any sample pairs of banks to merge is not more likely in a exposed than in a control tract. This assumption will not hold if the decision to merge is made because of specific tract characteristics of specific tracts in

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[17]They did not appear in Buchak et al. (2018) or Fuster et al. (2019) because these focused on earlier years and larger lenders

which branch networks overlap. For instance, if specific tract economic factors motivate the decision to merge that are also associated with lending.

The plausibility of the decision to merge being exogenous is necessary for the internal validity of the exposure instrument. However, the concern that post-merger decisions regarding the specifics branches to close is endogenous, does not represent a threat to the internal validity of the instrument. If the decision of any sample pairs of banks to merge is not more likely in exposed tracts relative to control tracts the internal validity of the instrument holds. However, if the post-merger election of branch closings is indeed related to specific tract characteristics this will represent a threat to the external validity of the identification strategy. I'll further discuss external validity later on in section 5.

To further address this challenge to identification (e.g., that the decision to merge is related to economic tract factors) I select only mergers between large banks. The final sample is formed by banks that at least have $50 billion in assets in the year before the merger approval. This situates them roughly in the top 1 percent of the size distribution of US banks. I keep only mergers between large banks because they are unlikely to be motivated by tract-level economic conditions. They tend to be driven by other factors such as: increase in market power, the generation of complementary business or expansion into new markets. Although cost savings derived from consolidation may also be taken into account, it is very unlikely that the merger decision is based on tract-level economic considerations. Moreover, the business size that exposed tracts represent is relatively very small. In a similar study by Nguyen (2019) with a lower bank pre-merger assets threshold for inclusion of $10 bn, the author estimated that the median percentage of the buyer (target) banks' deposits help in exposed tracts prior to the merger is only 1.4 percent (3.5 percent). Therefore, it is highly unlikely that potential gains or savings in those tracts motivates the decision to merge.

I list sample mergers in Table 2. Included mergers are mergers that were approved during the 2000s (but before the financial crisis)[18], in which the two participating institutions had 2 or more branches, had $50 bn in pre-merger assets, and had overlapping networks in at least one census tract.

[Table 2 about here.]

Table 3 shows sample merger summary statistics. Sample banks are very large, the median buyer (target) bank holds $565 billion ($73 billion) premerger assets, has 2,554 branches (723), and operates in 15 different states (9), while the median for all US banks is $302 million, 4 branches, and 1 state of operation, respectively.

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[18]Mergers occurred in 2008 and later years were excluded from the sample

[Table 3 about here.]

I define exposed tracts of any merger as those in which both the buyer and the target bank had branches in the year preceding the merger. Figure 1 shows an illustration of the census tract allocation for the 2004 merger between JP Morgan and Bank One for a particular County —Collin County, TX. Both illustrations show a map of the county with census tracts delineated. However, the bottom map shows the geographical distribution of branches of JP Morgan (red diamonds), Bank One (blue diamonds), whereas the top map shows exposed (yellow) and control (blue) tract allocation. A census tract of Collin County is defined as exposed if it has both a branch from JP Morgan and Bank One in the premerger year.

[Table 4 about here.]

Column 3 in Table 4 shows that exposed tracts are similar to controls tracts in many relevant dimensions. However several differences still exist. Exposed tracts have a slightly lower percentage of college educated population, higher percentage of population below the poverty level, a lower median family income, less bank branches, a lower bank branch growth, and more bank mortgage originations than control tracts. Therefore, I first control for these differences, and simultaneously use a difference-in-difference (DiD) framework to compare lending outcomes in exposed and control tracts for the same county, premerger and postmerger, and I allow for time-varying trends based on premerger tract characteristics. Specifically, to identify the local average treatment effect of bank branch closings on mortgage supply of fintech, banks, and shadow-banks, I estimate 2SLS equations of the following form:

$$Mortgage_{tcmyl} = \sigma_t + (\mu_y \times \nu_c) + \mathbf{X}_t\lambda_y + \rho_{Post}(\widehat{Post_{my} \times Closing_{tcm}}) + \eta_{tcmyl} \qquad (1)$$

$$(Post_{my} \times Closing_{tcm}) = \alpha_t + (\gamma_y \times \kappa_c) + \mathbf{X}_t\beta_y + \delta_{Post}(Post_{my} \times Expose_{tcm}) + \epsilon_{tcm} \qquad (2)$$

where $Mortgage_{tcmyl}$ is mortgage lending to borrowers in tract t, county c, of merger m in year y, by lender type l; $Post_{my}$ is a dummy equal to 1 if year t occurs after merger m is approved by federal regulators; $Closing_{tcm}$ is an indicator equal to one if a bank branch closes in tract t, county c, after merger m; $Expose_{tcm}$ is an indicator equal to one if tract t is an exposed tract of merger m; σ_t are tract fixed effects; $(\mu_y \times \nu_c)$ are county-by-year fixed effects; $\mathbf{X}_t$ is a vector of pre-merger census tract characteristics whose effects are allowed to vary by year. The pre-merger tract characteristics in vector $\mathbf{X}_t$ are population, population density, percentage of minority population, percentage of college educated population, median family income, percentage of population 65 years old and over, percentage of rural population,

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percentage of unemployed population, percentage of population below poverty level, number of bank branches in the year before the merger is approved, and average annual bank branch growth in the two years preceding merger approval. Standard errors are clustered at the county level. Finally, the coefficient of interest δ_{Post} measures the post-closing mean shift in the level of lending for lender type l.

The first-stage equation has also a difference-in-difference specification, where the excluded instrument for the potentially endogenous interaction between the post-merger indicator $Post_{my}$ and the closing indicator $Closing_{tcm}$, is the interaction between $Post_{my}$ and the exposure to a merger indicator $Expose_{tcm}$; α_t are tract fixed effects; $(\gamma_y \times \kappa_c)$ are county-by-year fixed effects, and all other variables as previously defined.

In this DiD framework the identifying assumption is that outcomes of exposed tracts would have similar trends to those of control tracts in the absence of exposure to a merger.

5   Results

First stage   To allow for the analysis of pre-trends in the data, I estimate year-by-year DiD and present the results in event study plots. The primary specification throughout the rest of the paper is:

$$y_{tcmyl} = \sigma_t + (\mu_y \times \nu_c) + \mathbf{X}_t \lambda_y + \delta_\tau (D_{my}^\tau \times Expose_{tcm}) + \eta_{tcmyl} \tag{3}$$

where y_{iclmy} is an outcome for tract t, county c, of merger m in year y, by lender type l,; σ_t are tract fixed effects; $(\mu_y \times \nu_c)$ are county-by-year fixed effects; $\mathbf{X}_t$ is a vector of pre-merger census tract characteristics, previously defined, whose effects are allowed to vary by year; D_{my}^τ is a dummy equal to 1 if year y is τ years after merger m is approved by federal regulators; and $Expose_{tcm}$ is a dummy equal to one if t is an exposed tract of merger m. The range of τ is between -8 and 12. Standard errors are clustered at the county level. Finally, coefficient δ_τ measures the difference, conditional on controls, in outcome y between exposed and control tracts, τ years before or after a merger.

Figure 3 shows that in the five years before a merger, exposed tracts are not more likely than control tracts to experience a branch closing. However, after that, there is a sharp increase in the number of closings one year after the merger and a moderate one two years after. Then, for the rest of post-merger years in which we have a balanced panel (9 years post-merger), differences go back to zero up until year nine after merger approval (except in the fifth year where closings are lower in exposed tracts). Column 1 of Table 5 shows the corresponding point estimates. Since the maximum of closings for all sample tracts is

generally one, point estimates can be interpreted as the change in relative probability of a closing in exposed tracts relative to control tracts τ years since the merger was approved. I find that the probability of a closing in the first year after a merger is 27 percentage points higher in exposed tracts relative to control tracts, and 33 percent combining the effects of the first and second year. For the rest of post-merger years for which we have a full panel, I find that the relative probability change is zero, or negative in the fifth year after the merger.

[Figure 3 about here.]

To assess whether the decline in branch closings translates into a reduction in the number of branches I follow the same method as described above to plot Figure 4. This figure shows that there is also no evidence of pre-trends. It also shows that after a merger approval the number of branches in exposed tracts relative to control tracts is lower up until the third year. This concentration of the effects of a merger in the first three years is consistent with the previous literature Garmaise and Moskowitz (2006); Nguyen (2019). Column 2 of Table 5 shows the corresponding point estimates. These show a decrease in the number of branches in exposed relative to controls tracts, between the first and third post-merger years, that ranges between 0.24 and 0.38 branches.

[Figure 4 about here.]

Intention to treat effects   I then focus in the reduced form intention-to-treat effect of the exposure to post-merger branch consolidation. In table 6 I estimate equation 3 for mortgage lending by the three lender types and their total lending. Column 1 shows a significant negative reduced form effect, at the 90% level or above, for banks from the fourth year post-merger until the seventh year. The magnitude of the accumulated significant effects amounts to a reduction with respect to the bank baseline of 12% of mortgages for the overall period. The sign and significance of the effects are mirrored by those in column 1 of table 7, here the negative reduced form effect for banks in dollar volume for the same years amounts to a reduction with respect to the bank baseline of 17% in dollar volume of bank mortgages. Column 2 and 3 of tables 6 and 7 show no significant persistent effects for shadow banks and fintech lenders. Column 4 of table 6 also shows no significant effects in the total number of mortgage supply, however column 4 of table 7 shows that for the total dollar volume of mortgages, exposure to a merger translates into an overall significant reduction at the 90% of the total mortgages for the post-merger years fourth, sixth, and seventh, that amounts roughly to a 11% decrease with respect to the total mortgages dollar volume baseline.

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Local average treatment effects To identify the local average treatment effect of bank branch closings on mortgage lending, I estimate the 2SLS equations 1 and 2. Here, the coefficient of interest is the second stage effect of the incidence of bank branch consolidation on mortgage lending for each lender type. Columns 1 and 3 of Table 8 show, that the average closing is associated with a significant reduction at the 90% level of 16 bank mortgages and a significant increase of 3 fintech mortgages. Over the 9 years following a closing, this amounts to a total decrease of 151 bank mortgages and a 27 increase in fintech mortgages. Column 3 of Table 9 shows that the fintech increase in the number of mortgages translates also into a significant increase in the dollar volume of mortgages of $640,500. This increase amounts to a total of $5.7 million over the 9 year period. Compared to the annual bank mortgages baseline, the variation in number of mortgages corresponds to a 44% decrease for banks and a 8% increase for fintechs, and the increase in the volume of fintech mortgages corresponds to a %9 increase over the same benchmark. Columns 2 and 4 of Table 8 show that closings have no significant impact on shadow bank mortgages and in the total amount of mortgages.

To evaluate the effects of bank branch closings on mortgage lending for each lender type over time, in Table 8, I estimate a more flexible version of the 2SLS equation 1 by splitting the interaction of exposure to a merger and *Post* into a set of annual interactions with leads and lags:

$$Mortgage_{tcmyl} = \sigma_t + (\mu_y \times \nu_c) + \mathbf{X}_i \lambda_y + \delta_\tau (\overline{D^\tau_{my} \times Closing_{tcm}}) + \eta_{tcmyl} \qquad (4)$$

Columns 1 and 3 respectively show that the average closing is associated with a significant reduction of bank mortgages and with a significant increase in fintech mortgages. Specifically bank mortgages, from the fourth year post-merger up until the eight year, experience a significant accumulated decrease after a closing of 235 bank mortgages at the 90% level or above. This represents a decrease 69% with respect to the annual baseline mean for banks. Fintech mortgages experience a significant accumulated increase of 10 mortgages at the 90% level or above, after a closing in the third and fifth year post-merger. This represents an increase of 3% with respect to the annual baseline mean for banks (baseline mean for fintechs is 0). Columns 2 and 4 show that closings have no significant persistent impact on shadow bank mortgages and only a significant one, at the 90% level, in years fourth and sixth post-closings for the total amount of mortgage supply.

To test whether the effects of branch closings have also an impact the $ volume of mortgages I estimate the same flexible version of the 2SLS equation 1 In Table 11. The results closely mirror those for the number of mortgages; after the average closing bank mortgages experience a total accumulated decrease, significant at the 90% level or above, of $52 million between the fourth and seventh post-merger years, and a positive significant one for fintech

of \$2.7 million in the third and fifth post-merger years. This represents a decrease of 83% in bank mortgages and a 4.3% increase in fintech ones with respect to the annual baseline mean for banks.

Heterogeneity To examine how the impact of closings varies across demographic groups, in Table 14 I separately estimate the 2SLS equation 1 splitting the sample by the median according to a set of relevant demographic characteristics related to the predominant gender, age, and economic characteristics of the census tract.

I start the analysis by testing whether the impact of closings varies with tract economic and racial characteristics. This analysis is consistent with findings that show that low-income and minority buyers are especially reliant on relationship-intensive lending[19]. For banks column 1 shows that lower median income tracts are both, driving the effects of branch closings on branch credit, and experiencing a steeper reduction in bank mortgages after the average closing, compared to their baseline LATE. Crucially, column 4, shows that this steeper reduction in bank credit leads to an overall reduction of the mortgage supply in these poorer tracts. This result suggests that the loss of credit relationships caused by branch closures is especially severe for certain segments of the population. Bank borrowers, such as low income individuals, who especially benefit from a personal relation with branch officers and from the exchange of soft information that the presence of a branch facilitates, suffer a steeper reduction in credit.

I then test the effects for fintech. Column 3 shows that above median income tracts are the ones driving the effect positive effect in fintech mortgages after a branch closing. These results contrast with those of banks, here wealthier tracts are the only ones who receive the positive increase in fintech originations, and all in all paint a negative picture of the effects of branch closings for mortgage markets in disfavored areas, as they suffer a reduction in bank credit and do not benefit from the positive effect in fintech credit.

I then, proceed to test whether the effects of branch closings differ by the percentage of minority population and I find similar results. In column 1 I show that both, the effect of branch closings depresses more bank mortgages in below median white percentage tracts, and that these below median white percentage tracts are the ones that are driving the effect of branch closures. Moreover, column 4 shows that this bank mortgage supply reduction translates into an overall reduction of bank mortgage supply for these higher minority tracts. In turn, column 3 shows that tracts with more white percentage of population both also,

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[19]Nguyen (2019) shows that post-bank-branch-closings the decline in credit that follows is especially severe in tracts with lower median income and higher-fraction of minority households. Butcher and Muñoz (2017) show that credit histories of minority and low-income borrowers tend to be thinner. Bond and Townsend (1996) show that borrowers that live in low-income and minority neighborhoods rely more heavily in informal sources of credit.

drive the positive effect in fintech credit, and have a higher increase in fintech supply than the baseline. These results suggest similar implications as the ones for income, the loss of relationship seems to carry a higher cost for minorities, that both suffer a higher reduction of bank mortgages, do not benefit from the the increase in fintech originations, and end up being credit rationed compared to areas not exposed to a closing.

I continue the analysis measuring whether the effects differ by the percentage of female population. This analysis is consistent with findings that show that there is a gender gap in fintech lending[20]. In column 1 I show that both, the effect of branch closings depresses more bank mortgages in tracts with lower percentage of female population, and that precisely these tracts are the ones that are driving the effect of branch closures. Column 3 shows that tracts with lower female share of population are the ones driving the increase of fintech mortgages after a closing. These two results suggest that males seem to be the ones driving both the decrease of bank borrowing and the increase in fintech borrowing. After a bank closure males swiftly switch to new technology intensive provider types. Women seem to be more conservative in the approach to new lender types, and either go to another branch of the surviving institution or switch to a non-tech-intensive competitor.

Finally I test whether the effects of closings differs for senior population. I test this subgroup of the population since people over 60 uses less technology intensive channels to access banking services[21] and this could influence the adoption of fintech that follows a closing. In column 1 I show that in tracts with a less percentage of people 65 and over years old the reduction in mortgages caused by a branch closing is much steeper and is driving the overall effects. Moreover, this reduction in bank supply leads to a reduction of the overall mortgage supply for these areas. This suggests that the younger segments of the population are the ones that are switching lender types after a closing. Column 3 shows that tracts with less senior population are also driving the increase in fintech mortgages that follows a closing. These two findings suggest that the senior segment of the population, when facing a closing, does not substitute the lender type for a more technology intensive one. This could be supportive evidence of the preferences of these groups for the less technology intensive channels through which banking services have been traditionally provided.

Reverse causality   A potential threat to the validity of the identified effects of this study is that of reverse causality. If mergers, and thus post-merger closings, occur in areas in which fintech adoption is already higher, that could be biasing the estimated effects of branch closings. To rule out this possibility, in figure 5 I plot the annual number of fintech mortgages for all census tracts in my sample. The plot shows that fintech mortgages only start to

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[20]Chen et al. (2021) show that while 29% of men use fintech products and services, only 21% of women do.
[21]Dodini et al. (2016) show that only 18% of people over the age of 60 use mobile banking.

significantly increase for all tracts of all mergers in my sample after the second post-merger year. Therefore the threat of reverse causation is not a problem in this study, since fintech mortgage levels in all tracts for all pre-merger and merger approval years are zero an could not drive the decision to merge.

[Figure 5 about here.]

External validity Is the local average treatment effect (LATE) identified by exposure to post-merger branch consolidation representative of the more general effect of bank branch closings in all settings? To explore this I construct Table 12 and compare columns 2 and 3 to column 1. Merger sample tracts are more similar to tracts with bank branch closings than to all branched tracts in several dimensions. For instance compared to all branched tracts both sample and closing tracts, have more population, more percentage of college educated population, lower share of population below the poverty level, less share of rural population, more share of population 65 years old and over, lower unemployment rate, higher median family income, more bank branches, and larger bank and shadow bank mortgage markets. Only in relation to population density, the percentage of minority population, average branch growth, and in fintech originations there is no significant difference between all branched tracts and tracts with closings (and there is significant difference compared to sample merger tracts) or the sign of its difference varies compared to the one between sample tracts and tracts with closings.

[Table 12 about here.]

To further scrutinize the LATE identified I construct Table 13. In this table I compare complier tract characteristics to those of sample tracts —complier tracts are those that closed a branch if and only because they were an exposed tract. Although exposure to a merger is assumed to be exogenous to tract characteristics (and this assumption is sufficient for the internal validity of the merger instrument), the posterior decision to close a branch, and which particular branch to close need not be to be exogenous for the internal validity of the instrument to hod. I study this posterior selection because it affects the interpretation of the LATE. With heterogeneous treatment effects, the LATE identified by an instrument is the average treatment effect on the compliers. That is, the effect of closing a branch in an exposed tract that has closed a branch only because it has been affected by a merger —if it had not been affected it would not have closed the branch. Table 13 shows that complier tracts are remarkably similar to sample tracts. However, a few differences remain; complier tracts tend to be less densely populated, have less percent of rural population, and more bank branches. This last point suggests that post-merger closings of bank branches

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are more focused in over-branched tracts. This, in turn suggests that the estimated effects underestimates the impact of an average branch closing in the United States.

[Table 13 about here.]

6   Conclusion

The main contribution of this paper is to show that bank branch closings significantly change the lender mix of the mortgage market. Although closings do not affect the overall supply of mortgages of the market (Nguyen (2019)), this fact is obscuring an important change. I show that closings both, increase fintech supply and reduce bank supply, thus significantly changing the lender mix in the mortgage market. More specifically, I show that the average closing leads to an 8% increase in the number of fintech mortgages and to a 44% decrease in the number of bank mortgages in the 9 year period that follows the closing. These findings are consistent with the view that fintech is improving the products and services offered to the market and not only benefiting from regulation arbitrage, since fintech, and not bank competitors or shadow banks are filling the gap left by the closure of a branch and the comparisons that I make are between constant regulation areas.

But, does this change in the lender mix matter? I provide evidence that it does. I show that closings, change who gets credit and who no longer does. More specifically I show that the effects of a closing varies across population groups, and that crucially, this leads to credit rationing for certain segments of the population. Poorer and higher minority areas, both experience a more severe depression of bank credit and do not benefit from the increase in fintech credit after a branch closing. While, richer and lower minority areas are driving the increase in fintech credit. These findings are consistent with the literature on the importance of lending relationships in bank branch lending as bank-branch-customer relationships are specially important for information-intensive borrowers such as low-income and minority groups. They are also supporting evidence for the view that fintech lenders, by using new machine learning methods and other new technologies, are increasing the financial exclusion risk of certain segments of the population.

The last takeaway of this paper is that branch closings are significantly changing mortgage markets. Even in the fintech era, in which the financial industry is making an intensive use of technology, bank branches are still key for mortgage markets. This paper suggests that branches, by reducing information asymmetries, allow vulnerable to financial exclusion segments of the population to obtain credit. The findings in this paper have important implications for the financial industry as it shows that the branch network reduction tactic

followed by most banks is fostering the adoption of a new competitor type. This competitor is less regulated and employs a different set of tools that may jeopardize the future dominance of banks in mortgage markets.

The current wave of branch closings is far from being over, branch closings in the US are currently accelerating and are expected to continue in the following years. The role of bank branches is simultaneously being redefined, branches are being transformed by reducing the emphasis on the regular day to day operations and emphasizing the tailored service and commercial emphasis. Additionally, the financial industry is experiencing other key disruptions, larger corporations, with big advantage in data accumulation and data processing technology known as bigtech, are entering the financial services industry. In this paper I show that research on the interplay between incumbents in the industry, and the role of bank branches will still be important in the coming years. The final equilibrium resulting form the interplay between these forces shapes crucial outcomes for financial the financial industry and for the lives of most American citizens.

References

BAROCAS, S. AND A. D. SELBST (2016): "Big data's disparate impact," *Calif. L. Rev.*, 104, 671. 2, 6

BARTLETT, R., A. MORSE, R. STANTON, AND N. WALLACE (2021): "Consumer-lending discrimination in the FinTech Era," *Journal of Financial Economics*. 5, 6

BOND, P. AND R. M. TOWNSEND (1996): "Formal and informal financing in a Chicago neighborhood," *Economic Perspectives*, 20, 3–27. 15

BONFIM, D., G. NOGUEIRA, AND S. ONGENA (2020): "Sorry, We're Closed" Bank Branch Closures, Loan Pricing, and Information Asymmetries," *Review of Finance*, 25, 1211–1259. 2, 4

BUCHAK, G., G. MATVOS, T. PISKORSKI, AND A. SERU (2018): "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 130, 453–483. 2, 3, 5, 6, 8, 9

BUTCHER, K. F. AND A. P. MUÑOZ (2017): "Using Credit Reporting Agency Data To Assess the Link Between the Community Reinvestment Act and Consumer Credit Outcomes," *Cityscape*, 19(2), 85–108. 15

CHEN, S., S. DOERR, J. FROST, L. GAMBACORTA, AND H. S. SHIN (2021): "The fintech gender gap," BIS Working Papers 931, Bank for International Settlements. 16

DE ROURE, C., L. PELIZZON, AND A. V. THAKOR (2021): "P2P lenders versus banks: Cream skimming or bottom fishing?" SAFE Working Paper Series 206, Leibniz Institute for Financial Research SAFE. 5

DODINI, S., A. A. LOPEZ-FERNANDINI, E. A. MERRY, AND L. THOMAS (2016): "Consumers and Mobile Financial Services 2016," Reports and Studies 1777, Board of Governors of the Federal Reserve System (U.S.). 16

FUSTER, A., P. GOLDSMITH-PINKHAM, T. RAMADORAI, AND A. WALTHER (2021): "Predictably Unequal? The Effects of Machine Learning on Credit Markets," *The Journal of Finance*, n/a. 6

FUSTER, A., M. PLOSSER, P. SCHNABL, AND J. VICKERY (2019): "The Role of Technology in Mortgage Lending," *The Review of Financial Studies*, 32, 1854–1899. 2, 3, 5, 8, 9

GARMAISE, M. J. AND T. J. MOSKOWITZ (2006): "Bank Mergers and Crime: The Real and Social Effects of Credit Market Competition," *The Journal of Finance*, 61, 495–538. 13

IRANI, R. M., R. IYER, R. R. MEISENZAHL, AND J.-L. PEYDRÓ (2020): "The Rise of Shadow Banking: Evidence from Capital Regulation," *The Review of Financial Studies*, 34(5), 2181–2235. 5

JAGTIANI, J., L. LAMBIE-HANSON, AND T. LAMBIE-HANSON (2019): "Fintech Lending and Mortgage Credit Access," . 3, 8, 9

MORGAN, D. P., M. L. PINKOVSKIY, AND B. YANG (2016): "Banking Deserts, Branch Closings, and Soft Information," Liberty Street Economics 20160307, Federal Reserve Bank of New York. 2, 5

NGUYEN, H.-L. Q. (2019): "Are credit markets still local? Evidence from bank branch closings," *American Economic Journal: Applied Economics*, 11, 1–32. 2, 3, 4, 5, 9, 10, 13, 15, 18

7 Figures

Figure 1: Exposed and Control Tracts Selection
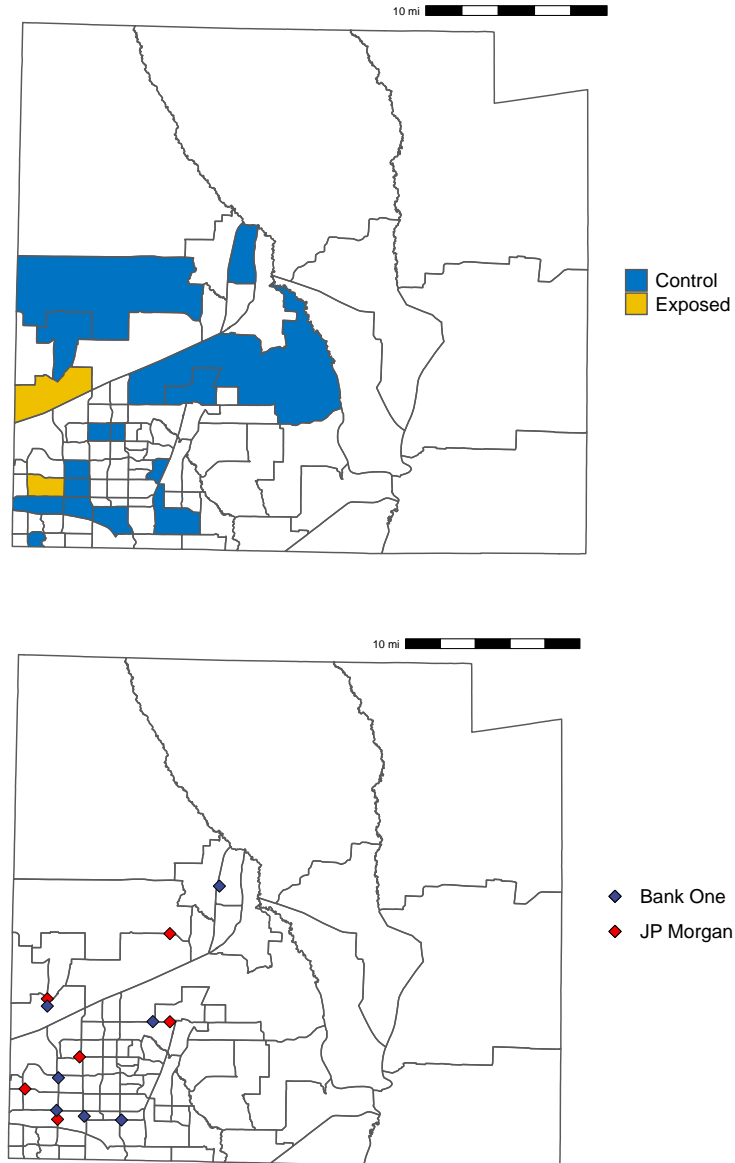
Notes: The map on the top shows control tracts (blue) and exposed tracts (yellow) in Collin County, Texas for the sample merger between JP Morgan and Bank One, that was approved in 2004. The map on the bottom shows the network of the merger banks in the year before merger approval.

Figure 2: Fintech Classification Method
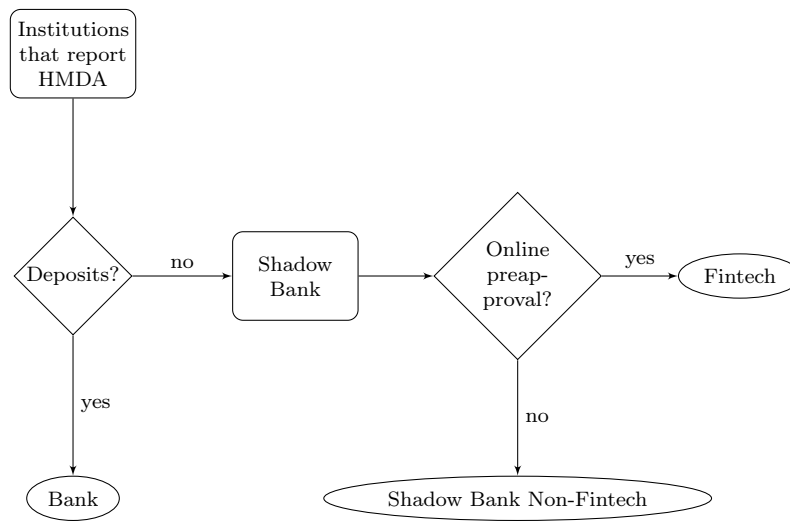
Figure 3: Exposure to Consolidation and Bank Branch Closings
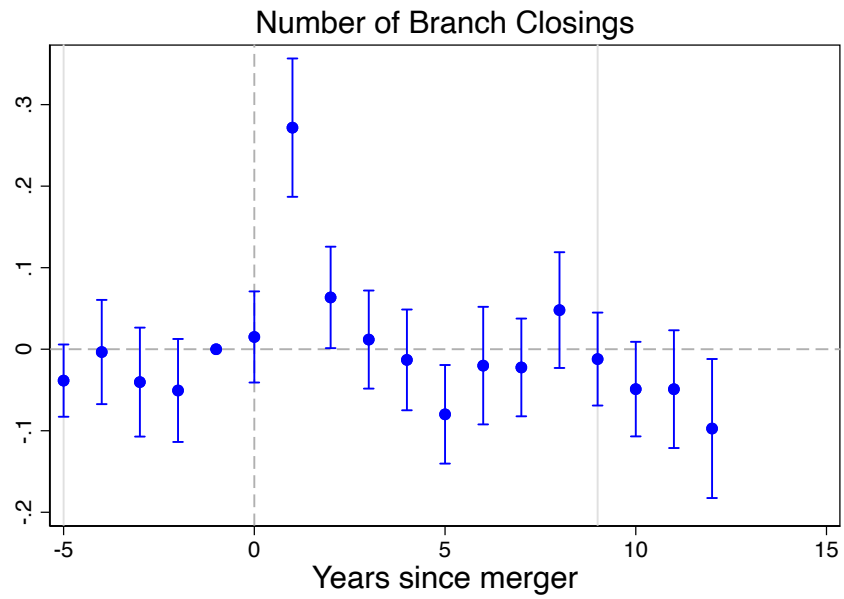
Notes: This figure plots the first-stage relationship between exposure to consolidation and the incidence of branch closings, obtained from estimating equation 3. The bars show 95 percent confidence intervals, $\tau = 0$ is the year the merger was approved by federal regulators, and all coefficients are normalized relative to $\tau = -1$. Robust standard errors are clustered at the county level.

Figure 4: Exposure to Consolidation and Bank Branch Levels
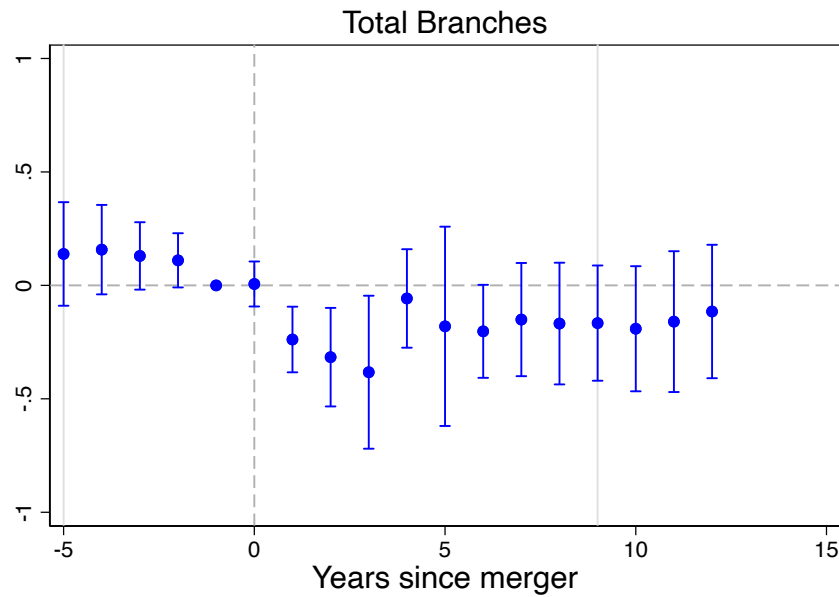
Total Branches

Notes: This figure plots the first-stage relationship between exposure to consolidation and the total number of branches, obtained from estimating equation 3. The bars show 95 percent confidence intervals, $\tau = 0$ is the year the merger was approved by federal regulators, and all coefficients are normalized relative to $\tau = -1$. Robust standard errors are clustered at the county level.

Figure 5: Number of Fintech Mortgages in Sample Tracts
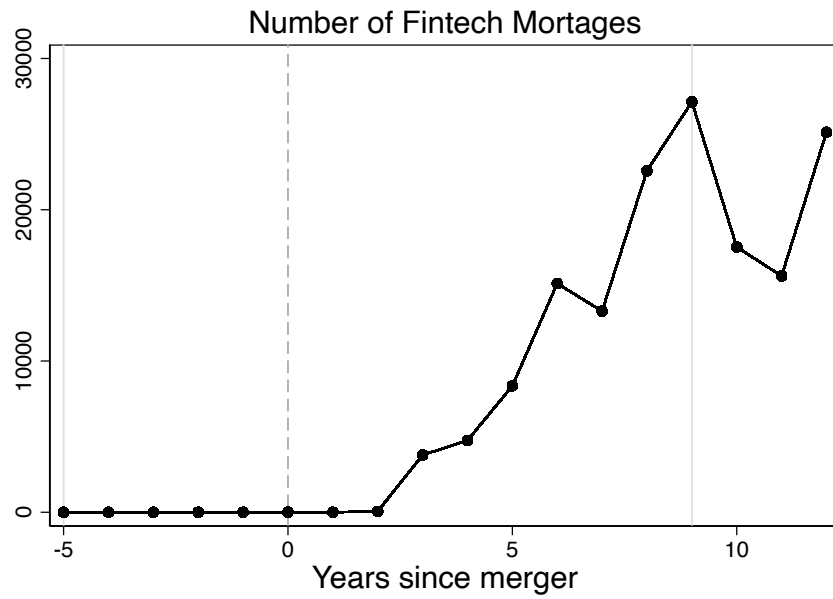
Notes: This figure plots the number of fintech mortgages in sample tracts for every year relative to the merger approval. $\tau = 0$ is the year the merger was approved by federal regulators.

8 Tables

Table 1: Sample Fintech Lenders

Lender	Fintech Starting Year			
	Buchak et al. (2018)	Fuster et al. (2019)	Jagtiani et al. (2019)	This paper
AmeriSave Mortgage	2008		2008	2008
Better Mortgage	not included		2016	2016
CashCall Inc.	2008		2008	2008
Everett Financial		2016	2016	2016
Guaranteed Rate	2008	2010	2010	2010
loanDepot		2016	2016	2016
Movement Mortgage	2013	2014	2014	2014
Sofi	not included	not included	2016	2016
Quicken	2000	2010	2010	2010

Notes: This table shows three different listings of sample fintech providers and their starting year as fintech institution type. This paper follows Jagtiani et al. (2019) fintech classification
Source: Buschak et al. (2018), Fuster et al. (2019), & Jagtiani et al.(2019).

Table 2: Sample Mergers

Buyer	Target	Year approved
Bank of America	Fleet National Bank	2004
JPMorgan Chase Bank	Bank One	2004
Wachovia Bank	SouthTrust Bank	2004
Regions Bank	AmSouth Bank	2006
Bank of America	LaSalle Bank	2007

Notes: This table shows the 5 mergers included in the sample and the year they were approved by federal regulators.

Table 3: Mergers Summary Statistics

	Median	Min	Max
Panel A: Buyer			
Total assets ($bn)	565	81	1,200
Branches	2,554	594	5,723
States of operation	15	4	31
Counties of operation	401	47	698
Panel B: Target			
Total assets ($bn)	73	52	257
Branches	723	138	1,563
States of operation	9	1	13
Counties of operation	134	7	188

Notes: The table displays summary statistics for the 5 buyer and 5 target banks in the merger sample. All variables are as of the year in which the intention to merge was announced.

Table 4: Tract Summary Statistics: Exposed vs. Control

Variable	(1) Exposed	(2) Control	(3) p-value on difference
Population	5,752	5,539	0.519
	[3,766]	[2,872]	
Population density	2,498	6,309	0.290
	[3,544]	[17,296]	
Percent minority	28.1	29.3	0.935
	[23.2]	[23.7]	
Percent college educated	59.1	60.9	0.034
	[19.1]	[18.6]	
Percent poverty level	13.3	10.2	0.019
	[11.6]	[9.1]	
Percent rural population	5.8	3.2	0.024
	[16.1]	[11.7]	
Percent population 65 and over	16.3	16.0	0.581
	[11.9]	[13.3]	
Percent unemployed	5.9	5.0	0.184
	[6.4]	[5.5]	
Median income (000s)	56.43	61.1	0.052
	[27.64]	[29.9]	
Percent MSA median income	117.1	119.0	0.074
	[49.6]	[55.5]	
Total branches	6.9	4.0	0.000
	[4.5]	[2.3]	
Branch growth	0.041	0.076	0.003
	[0.114]	[0.198]	
Bank mortgages	339.5	306.4	0.012
	[480.2]	[315.1]	
Shadow bank mortgages	119.6	116.7	0.134
	[189.8]	[142.3]	
Fintech mortgages	0	0	n.a.
	[0]	[0]	
Observations	418	1,982	

Notes: Standard deviations are in brackets. Column 3 reports the *p*-value for the difference between columns 1 and 2. Here *p*-values are obtained from a regression of tract characteristics on an indicator for being an exposed tract and county fixed effects. Population density is per square mile. Percent MSA median income is the ratio of tract median income to MSA median income. Growth rates are the average annual growth rates over the two years preceding the merger approval. All demographic variables are as of the 2000 census. Credit variables are as of the year before federal merger approval.

Table 5: First Stage Estimates

	(1) Number branch closings	(2) Total branches
$\delta_{<-1}$	-0.024	0.124
	(0.021)	(0.092)
δ_0	0.015	0.009
	(0.028)	(0.050)
δ_1	0.271***	-0.236***
	(0.043)	(0.074)
δ_2	0.063**	-0.314***
	(0.031)	(0.109)
δ_3	0.011	-0.381**
	(0.030)	(0.171)
δ_4	-0.014	-0.056
	(0.031)	(0.110)
δ_5	-0.081***	-0.178
	(0.031)	(0.223)
δ_6	-0.021	-0.200*
	(0.036)	(0.104)
δ_7	-0.023	-0.148
	(0.030)	(0.126)
δ_8	0.047	-0.165
	(0.036)	(0.136)
δ_9	-0.013	-0.165
	(0.029)	(0.128)
$\delta_{>9}$	-0.061**	-0.165
	(0.026)	(0.138)
Tract FEs	Yes	Yes
County $\times$ Year FEs	Yes	Yes
Observations	42,462	42,462
R^2	0.25	0.85
Baseline mean	0.3	6.9

Notes: This table shows estimates of equation 3. All coefficients are normalized relative to $\tau = -1$, and $\tau = 0$ is the year in which the merger was approved by federal regulators. The baseline mean is calculated for exposed tracts in $\tau = -1$. Robust standard errors are clustered at the county level and are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Reduced Form Estimates

| | Reduced Form | | | |
	(1) Bank Mortgages	(2) Shadow bank Mortgages	(3) Fintech Mortgages	(4) Total Mortgages
$\delta_{<-1}$	-2.426	-1.406	-0.333	-4.164
	(6.942)	(2.445)	(0.209)	(8.995)
δ_0	4.281	-0.900	-0.0728	3.308
	(4.903)	(2.489)	(0.151)	(6.932)
δ_1	4.727	5.004	-0.0385	9.693
	(7.779)	(5.225)	(0.148)	(12.48)
δ_2	2.276	4.172	-0.0261	6.421
	(9.347)	(5.720)	(0.154)	(14.15)
δ_3	-4.428	-2.024	0.917	-5.535
	(7.143)	(3.097)	(0.610)	(10.01)
δ_4	-10.60*	-3.244	0.602	-13.24
	(6.049)	(3.234)	(0.429)	(9.001)
δ_5	-11.00**	-2.216	1.494	-11.72
	(5.547)	(3.929)	(0.909)	(9.002)
δ_6	-9.160*	-3.232	0.240	-12.15
	(5.212)	(3.119)	(0.369)	(7.906)
δ_7	-9.140*	-2.666	0.604*	-11.20
	(4.881)	(3.072)	(0.329)	(7.384)
δ_8	-7.482	-1.379	0.665	-8.196
	(4.522)	(3.137)	(0.578)	(6.823)
δ_9	-5.170	1.071	0.565	-3.534
	(4.943)	(3.524)	(0.495)	(7.905)
$\delta_{>9}$	-2.111	0.0906	0.259	-1.762
	(8.936)	(3.514)	(0.854)	(11.07)
Tract FEs	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Observations	42,462	42,462	42,462	42,462
R^2	0.91	0.85	0.72	0.90
Baseline mean	339.5	119.6	0	459.1

Notes: This table shows estimates of equation 3. All coefficients are normalized relative to $\tau = -1$, and $\tau = 0$ is the year in which the merger was approved by federal regulators. The baseline mean is calculated for exposed tracts in $\tau = -1$. Robust standard errors are clustered at the county level and are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Reduced Form Estimates

	Reduced Form			
	(1) Bank Mortgages $(000s)	(2) Shadow bank Mortgages $(000s)	(3) Fintech Mortgages $(000s)	(4) Total Mortgages $(000s)
$\delta_{<-1}$	-1,207.6	-202.6	-76.0	-1,486.2
	(1,682.4)	(511.8)	(57.5)	(2,106.4)
δ_0	1,336.8	1.1	-7.1	1,330.8
	(1,253.2)	(456.3)	(37.2)	(1,530.4)
δ_1	934.1	1,025.6	1.4	1,961.1
	(2,237.4)	(1,031.5)	(36.3)	(3,112.6)
δ_2	1,821.3	1,154.5	5.8	2,981.6
	(2,851.0)	(1,399.9)	(37.9)	(3,988.4)
δ_3	-921.0	-140.7	254.1	-807.5
	(2,301.6)	(713.7)	(168.9)	(2,951.4)
δ_4	-2,943.7**	-746.6	144.2	-3,546.1*
	(1,474.8)	(570.5)	(120.4)	(1,955.0)
δ_5	-3,169.0**	-483.5	410.0	-3,242.4
	(1,526.0)	(793.9)	(252.4)	(2,089.5)
δ_6	-2,314.6*	-837.0	53.1	-3,098.5*
	(1,342.8)	(518.0)	(110.8)	(1,651.7)
δ_7	-2,372.4**	-220.5	140.8	-2,452.1*
	(1,161.2)	(529.8)	(87.5)	(1,478.3)
δ_8	-1,281.2	-43.9	69.1	-1,256.0
	(1,196.0)	(734.8)	(131.6)	(1,647.2)
δ_9	-1,304.6	243.3	76.1	-985.2
	(1,210.7)	(881.9)	(118.8)	(1,807.8)
$\delta_{>9}$	-846.2	420.2	3.5	-422.5
	(2,299.6)	(1,019.9)	(238.9)	(2,896.5)
Tract FEs	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Observations	42,462	42,462	42,462	42,462
R^2	0.88	0.80	0.67	0.87
Baseline mean	63,222.6	20,015.9	0.0	83,238.5

Notes: This table shows estimates of equation 3. All coefficients are normalized relative to $\tau = -1$, and $\tau = 0$ is the year in which the merger was approved by federal regulators. The baseline mean is calculated for exposed tracts in $\tau = -1$. Robust standard errors are clustered at the county level and are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Second Stage Estimates - Mortgage Originations

	2SLS			
	(1) Bank Mortgages	(2) Shadow bank Mortgages	(3) Fintech Mortgages	(4) Total Mortgages
Post $\times$ Closing	-16.87*	2.721	3.001***	-11.15
	(8.727)	(5.284)	(0.810)	(12.88)
Tract FEs	Yes	Yes	Yes	Yes
County $\times$ Year FEs	Yes	Yes	Yes	Yes
First-Stage F stat.	1,538	1,538	1,538	1,538
Observations	42,462	42,462	42,462	42,462
R^2	0.42	0.31	0.35	0.38
Baseline mean	339.5	119.6	0	459.1

Notes: This table shows estimates of equation 1. The baseline mean is calculated for exposed tracts in $\tau = -1$. Robust standard errors are clustered at the county level and are in parentheses.

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Second Stage Estimates - Mortgage Originations Volume

	2SLS			
	(1) Bank Mortgages $(000s)	(2) Shadow bank Mortgages $(000s)	(3) Fintech Mortgages $(000s)	(4) Total Mortgages $(000s)
Post × Closing	-2,716.26 (2,487.45)	901.59 (1,236.08)	640.50*** (222.10)	-1,174.17 (3,359.50)
Tract FEs	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
First-Stage F stat.	1,538	1,538	1,538	1,538
Observations	42,462	42,462	42,462	42,462
R^2	0.22	0.19	0.30	0.22
Baseline mean	63,222.64	20,015.87	0.00	83,238.51

Notes: This table shows estimates of equation 1. The baseline mean is calculated for exposed tracts in $\tau = -1$. Robust standard errors are clustered at the county level and are in parentheses.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Second Stage Dynamic Estimates - Mortgage Originations

	2SLS			
	(1) Bank Mortgages	(2) Shadow bank Mortgages	(3) Fintech Mortgages	(4) Total Mortgages
$\delta_{<-1}$	-19.54	-8.614	-0.679	-28.83
	(19.99)	(12.08)	(1.851)	(29.48)
δ_0	0.526	-5.656	0.549	-4.581
	(23.14)	(13.98)	(2.142)	(34.14)
δ_1	1.544	11.82	0.953	14.31
	(21.12)	(12.76)	(1.955)	(31.15)
δ_2	-7.782	8.574	1.079	1.871
	(23.00)	(13.90)	(2.130)	(33.94)
δ_3	-29.02	-9.242	4.222*	-34.04
	(23.42)	(14.15)	(2.169)	(34.56)
δ_4	-48.83**	-13.30	3.032	-59.09*
	(23.62)	(14.27)	(2.187)	(34.85)
δ_5	-52.12**	-11.48	6.136***	-57.46
	(23.76)	(14.36)	(2.200)	(35.05)
δ_6	-47.94**	-14.85	2.231	-60.56*
	(23.80)	(14.38)	(2.203)	(35.11)
δ_7	-47.67**	-12.47	3.526	-56.62
	(23.80)	(14.38)	(2.204)	(35.12)
δ_8	-41.34*	-8.868	3.363	-46.85
	(23.73)	(14.34)	(2.198)	(35.02)
δ_9	-33.81	-1.108	3.067	-31.85
	(23.68)	(14.31)	(2.192)	(34.93)
$\delta_{>9}$	-23.38	-3.537	2.061	-24.86
	(21.23)	(12.83)	(1.966)	(31.32)
Tract FEs	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
First-Stage F stat.	61.49	61.49	61.49	61.49
Observations	42,462	42,462	42,462	42,462
R^2	0.41	0.30	0.34	0.38
Baseline mean	339.5	119.6	0	459.1

Notes: This table shows estimates of equation 4 splitting the interaction of exposure to a merger and *Post* into a set of annual interactions with leads and lags. All coefficients are normalized relative to $\tau = -1$, and $\tau = 0$ is the year in which the merger was approved by federal regulators. The baseline mean is calculated for exposed tracts in $\tau = -1$. Robust standard errors are clustered at the county level and are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Second Stage Dynamic Estimates - Mortgage Originations Volume

	2SLS			
	(1) Bank Mortgages $(000s)	(2) Shadow bank Mortgages $(000s)	(3) Fintech Mortgages $(000s)	(4) Total Mortgages $(000s)
$\delta_{<-1}$	-7,527.6	-1,109.5	-171.9	-8,809.1
	(5,696.2)	(2,824.7)	(507.3)	(7,691.8)
δ_0	785.4	-105.0	143.1	823.6
	(6,595.0)	(3,270.4)	(587.3)	(8,905.5)
δ_1	-564.0	2,817.6	245.7	2,499.4
	(6,018.8)	(2,984.7)	(536.0)	(8,127.5)
δ_2	1,721.9	3,082.0	275.1	5,079.1
	(6,556.1)	(3,251.2)	(583.8)	(8,853.1)
δ_3	-7,003.2	-668.8	1,104.7*	-6,567.3
	(6,676.1)	(3,310.6)	(594.5)	(9,015.0)
δ_4	-13,018.7*	-2,543.2	697.5	-14,864.4
	(6,732.4)	(3,338.6)	(599.5)	(9,091.0)
δ_5	-14,415.8**	-1,889.1	1,601.5***	-14,703.4
	(6,771.4)	(3,357.9)	(603.0)	(9,143.7)
δ_6	-12,190.1*	-3,134.5	461.2	-14,863.4
	(6,782.6)	(3,363.5)	(604.0)	(9,158.9)
δ_7	-12,539.8*	-1,118.7	787.4	-12,871.1
	(6,784.4)	(3,364.4)	(604.2)	(9,161.3)
δ_8	-8,858.6	-602.6	467.8	-8,993.3
	(6,764.9)	(3,354.7)	(602.4)	(9,135.0)
δ_9	-8,834.7	445.6	487.7	-7,901.4
	(6,748.0)	(3,346.3)	(600.9)	(9,112.1)
$\delta_{>9}$	-7,008.1	982.3	250.2	-5,775.6
	(6,051.3)	(3,000.8)	(538.9)	(8,171.4)
Tract FEs	Yes	Yes	Yes	Yes
County $\times$ Year FEs	Yes	Yes	Yes	Yes
First-Stage F stat.	61.49	61.49	61.49	61.49
Observations	42,462	42,462	42,462	42,462
R^2	0.21	0.19	0.29	0.21
Baseline mean	63,222.6	20,015.9	0.0	83,238.5

Notes: This table shows estimates of equation 4. All coefficients are normalized relative to $\tau = -1$, and $\tau = 0$ is the year in which the merger was approved by federal regulators. The baseline mean is calculated for exposed tracts in $\tau = -1$. Robust standard errors are clustered at the county level and are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Representativeness of the Merger Sample

Variable	(1) All branched tracts	(2) Tracts with closings	(3) Merger sample
Population	4,680	4,929	5,634
	[2,195]	[2,448]	[3,074]
Population density	4,026	3,484	5,913
	[10,242]	[7,222]	[16,556]
Percent minority	24.8	24.5	29.7
	[25.6]	[23.7]	[24.0]
Percent college educated	51.7	54.5	60.9
	[18.2]	[18.4]	[19.0]
Percent poverty level	12.0	11.7	10.8
	[10.0]	[10.3]	[9.9]
Percent rural population	24.1	14.2	3.8
	[38.0]	[29.6]	[12.9]
Percent population 65 and over	13.9	14.6	15.2
	[7.4]	[8.4]	[11.9]
Percent unemployed	5.7	5.6	5.2
	[4.8]	[5.0]	[5.7]
Median income (000s)	52.70	54.84	60.81
	[23.02]	[24.12]	[30.09]
Percent MSA median income	104.2	107.2	119.4
	[38.1]	[40.8]	[55.4]
Total branches	2.30	3.58	4.28
	[2.08]	[3.04]	[2.96]
Branch growth	0.022	0.021	0.055
	[0.147]	[0.173]	[0.175]
Bank mortgages	258.6	296.3	356.0
	[260.8]	[317.2]	[400.1]
Shadow bank mortgages	77.8	89.1	114.9
	[103.3]	[123.6]	[147.0]
Fintech mortgages	0	0	0
	[0]	[0]	[0]
Observations	37,537	8,704	2,192

Notes: Standard deviations are in brackets. demographic variables are as of the 2000 census; all other variables are from 2003. Columns 1 and 2 are all tracts in the United States that were branched and had a closing, respectively, over the 2003-2008 period.

Table 13: Complier Characteristics

Variable	(1) Proportion of compliers above the sample median (percent)	(2) Ratio: Compliers to sample
Population	60.6	1.21
Population density	23.8	0.48
Percent minority	47.5	0.95
Percent college educated	53.9	1.08
Percent poverty level	57.1	1.14
Percent rural population	30.9	0.62
Percent population 65 and over	54.8	1.10
Percent unemployed	47.9	0.96
Median income (000s)	47.9	0.96
Percent MSA median income	51.9	1.04
Total branches	84.8	1.70
Branch growth	50.3	1.01
Bank mortgages	60.7	1.21
Shadow bank mortgages	58.3	1.17
Fintech mortgages	0	0

Notes: This table shows how complier tracts compare to the median tract in the sample. Complier characteristics are calculated using the methodology outlined in Angrist and Pischke (2009). Column 1 shows the proportion of compliers who lie above the median tract in the sample; column 2 calculates the ratio of compliers to sample by dividing each entry in column 1 by 0.50. Demographic variables are as of 2000 census; total branches and branch growth are as of the year preceding each merger.

Table 14: Second Stage Splits: Demographic

| | Mortgage Originations | | | | |
| | Banks | Shadow banks | Fintechs | Total | Observations |
	(1)	(2)	(3)	(4)	(5)
Baseline	-16.87*	2.721	3.001***	-11.15	42,462
Median income					
Above median	-2.625	-0.799	2.464**	-0.961	20,466
	(10.46)	(6.859)	(1.111)	(15.93)	
Below median	-27.07***	-0.670	0.0448	-27.69**	21,492
	(8.811)	(4.800)	(0.565)	(12.42)	
White percentage					
Above median	-5.423	-0.611	4.783***	-1.250	21,312
	(12.08)	(7.206)	(1.164)	(17.66)	
Below median	-20.00**	-9.109*	-1.090	-30.20**	20,646
	(8.450)	(5.241)	(0.733)	(12.76)	
Percentage female population					
Above median	17.81	10.15*	0.0254	27.99*	21,258
	(10.98)	(5.879)	(0.945)	(15.43)	
Below median	-26.62***	1.157	3.245***	-22.22	20,430
	(9.319)	(5.893)	(0.881)	(14.01)	
Percentage population 65 and over					
Above median	1.414	4.846	0.488	6.748	21,600
	(9.911)	(5.050)	(0.761)	(13.72)	
Below median	-33.52***	-2.337	2.198**	-33.66**	20,124
	(10.61)	(7.093)	(1.071)	(16.35)	

Notes: This table shows estimates of equation 1. Baseline controls for the corresponding dependent variable in bold are omitted in each corresponding panel. Robust standard errors are clustered at the county level and are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Contents (Appendix)

Appendices

A Background

Table A1: Tract Summary Statistics: Exposed vs. All other

Variable	(1) Exposed	(2) All other	(3) p-value on difference
Population	5,752	4,702	0.000
	[3,766]	[2,523]	
Population density	2,498	6,534	0.111
	[3,544]	[16,460]	
Percent minority	28.1	43.2	0.000
	[23.2]	[32.0]	
Percent college educated	59.1	52.5	0.000
	[19.1]	[20.4]	
Percent poverty level	13.3	14.5	0.025
	[11.6]	[12.9]	
Percent rural population	5.8	8.7	0.000
	[16.1]	[23.8]	
Percent population 65 and over	16.3	13.0	0.000
	[11.9]	[10.1]	
Percent unemployed	5.9	6.9	0.095
	[6.4]	[7.0]	
Median income (000s)	56.43	51.40	0.000
	[27.64]	[26.63]	
Percent MSA median income	117.1	102.1	0.000
	[49.6]	[50.2]	
Total branches	6.9	1.2	0.000
	[4.5]	[1.8]	
Branch growth	0.041	0.032	0.022
	[0.114]	[0.187]	
Bank mortgages	339.5	211.0	0.000
	[480.2]	[229.8]	
Shadow bank mortgages	119.6	85.8	0.000
	[189.8]	[102.1]	
Fintech mortgages	0	0	n.a.
	[0]	[0]	
Observations	418	11,737	

Notes: Standard deviations are in brackets. Column 3 reports the p-value for the difference between columns 1 and 2. H[...]
a regression of tract characteristics on an indicator for being an exposed tract and county fixed effects. Population dens[...]
MSA median income is the ratio of tract median income to MSA median income. Growth rates are the average annual g[...]
preceding the merger approval. All demographic variables are as of the 2000 census. Credit variables are as of the year b[...]