# Fintech, Bank Branch Closings, and Mortgage Markets *

Josep Gisbert†

Universitat Pompeu Fabra and Barcelona SE

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**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 (U.S. Census tracts are small, relatively permanent statistical subdivisions of a county) 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% relative to non-closure tracts in the nine years that follow a closing, while bank mortgage lending falls by 44%, off an annual baseline of 340 mortgages. Fintech mortgage growth is driven by wealthier areas and areas with relatively smaller populations of women, seniors, and minorities.

Keywords: *Fintech, credit markets, branch closings, digital banking*

JEL Classification: D14, G21, G23, G51

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†Universitat Pompeu Fabra and Barcelona School of Economics. E-mail: josep.gisbert@upf.edu

# 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 characterized 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's share of the mortgage market has exploded in the last two decades, from a zero market share in the early 2000s to nowadays representing more than 12% of the overall US mortgage market[2].

Given the significance of these 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), a reduction of local credit supply (Nguyen 2019), the creation of "banking deserts"[3] (Morgan et al. 2016), and to severe contractions of credit for low income and minority groups (Nguyen 2019). Fintech has been linked to improvements in the efficiency of credit markets (Fuster et al. 2019), discrimination to minorities in the interest rate charged Bartlett et al. (2021), or regulatory arbitrage (basing its growth on the lower regulation that fintech has relative to banks), which could lead to financial instability. In this paper, I study whether these two disruptions, which have been viewed in isolation, are related. 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 strength, profitability, and stability of the overall US financial system as the 2007-2009 financial crisis portrayed.

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. HMDA data 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

[1]Closings amount to a total of 10,631 for the 2008-2020 period.

[2]According to the 2015 Home Mortgage Disclosure Act data.

[3]Areas with no bank branch within 10 miles.

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

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).

The instrument exploits closings due to the merger of two large, national banks that operated branches in close geographical proximity. 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 very 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 U.S. banks. The business size of exposed tracts represents such a minimal share of the participating bank's 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 into three types: banks, shadow banks, or fintech using established methods in the literature (Buchak et al. 2018; Fuster et al. 2019; Jagtiani et al. 2019).

[Figure 1 about here.]

As both banks and fintech lenders are competitors in the mortgage market, the first question that I explore is whether banks are fostering fintech's growth by deserting certain areas with branch closings. 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 especially 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.

My main results are as follows: first, I show that branch closings increase local mortgage fintech adoption persistently. Fintech mortgages increase by 8% on the aggregate in the nine years that follow a closing out of an annual baseline of 340 bank mortgages (I use bank mortgages as a baseline since there are no fintech mortgages in any sample tracts in all pre-merger years). 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 follow produces a decrease of 44% in the number of bank mortgages compared to the annual baseline (and relative to control tracts). This finding highlights the critical role of branches, which, even in the fintech era, seem to help 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 differ across population groups. After closings, poor, high minority, low share of female, and older populated areas suffer a steeper reduction of bank mortgages than the average area in the study. However, wealthy, 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 significant consequences for the type of borrower that can get a mortgage post-closing and, even more importantly, for those that no longer can get one. These findings also further raise 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 paper's main contribution, I show that previous tests that documented 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. This study shows 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, which increases it. This finding is evidence of the critical role of bank branches. Even in this fintech era characterized by the intensive use of technology and new channels to reach customers, bank branches still fulfill an important role in mortgage markets. In this paper, I show that the branch role of facilitating bank-branch-borrower relationships and the transmission of soft information is important for firm credit outcomes and household ones despite the presence of new technological advancements in the mortgage market.

Second, I contribute to identifying the elements that explain the rapid growth of fintech in credit markets. In a more positive light about this topic, new technology and improved methods could be the primary source of fintech growth. Precisely these new technologies could be the factor that allows fintech lenders to produce better services or to lend more cheaply to borrowers. Supporting this view, 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. Additionally, Buchak et al. (2018) show that fintech uses new technology to provide credit and attribute part of their growth to this use. Yet, another view is that fintech lenders are engaging in regulatory arbitrage. Fintech lenders may be benefiting from their lower regulation relative to banks to capture part of their market share in credit markets. For instance, Buchak et al. (2018) shows 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. 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. I make comparisons between areas with the same regulation and show that after a branch closing, fintech lenders, and not other banks, are the ones that capture the "deserted" borrowers. These findings suggest that fintech lenders provide better products or offer cheaper mortgages and do not base their growth exclusively on regulatory arbitrage.

Third, my analysis also contributes to the literature on the effects of fintech and bank branch closings on financial inclusion[5]. Generally, the literature on the effects of closings paints a negative light on its impact on financial inclusion. Nguyen (2019) shows that bank branch closings disproportionately reduce access to credit to information-intensive borrowers, such as minorities and low-income individuals. Morgan et al. (2016) show that, especially in low-income areas, credit can be rationed after branch closings due to the creation of banking deserts[6]. In contrast, some of the literature on fintech paints a positive light about its effects on financial inclusion. Bartlett et al. (2021) show that fintech lenders reduce disparities in the interest rate charged and do not discriminate in mortgage application rejection for Latinx/African-Americans compared to risk-equivalent borrowers. Yet, there is a more pessimistic view about the effects of fintech on financial inclusion too. Work by Barocas and Selbst (2016) portraits the negative effects of algorithm decision-making for the financial inclusion of large segments of the US population. Buchak et al. (2018) show that fintech lenders are less likely to serve less creditworthy FHA borrowers and higher unemployment geographies. Bartlett et al. (2021) show that fintech providers discriminate in the interest rate charged to Latinx/African-Americans. Finally, Fuster et al. (2021) recently tested the role of machine learning models in financial inclusion. They found that Black and

[5]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. Source: The World Bank.

[6]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.

Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning. 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 U.S. 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 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

[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 U.S. census borders (1990 or 2010 census) I use a set of relationship files provided by the U.S. census that show how the different census geographies relate to each other and allow to merge geographic entities over time.

[10]The rest of the 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

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 borrowers' location and not on that of the lender. That HMDA data is based on the borrowers' location allows me to estimate the impact of a branch closing on mortgage supply to borrowers 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 the Farm Service or Rural Housing Service. I then aggregate the remaining mortgages to create a yearly census tract-level measure of mortgage originations. Finally, I winsorize this measure 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 branch's address, the GPS coordinates of the location of the branch (only from 2008 onwards), and information related to the institution that owns the branch. I use GIS software to locate bank branches for which the GPS coordinates are available in the SOD. For branches whose GPS coordinates are not available, I use a combination of Google Maps Geocoding API (to find a branch's GPS coordinates using its address information) and GIS software to locate its census tract. The percentage of non-located branches in the complete 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 branch's 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 downloaded from FDIC's API all mergers with effective dates of inclusion in the

exceeds the loan volume threshold) in each of the two preceding calendar years. For-profit mortgage-lending institutions other than 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.

1999-2020 period[13]. I obtain federal approval dates by searching for the corresponding order of approval documents released by the FED, a press release by participants in the merger, or other regulators' press release notes. I gather merger announcement dates by searching the announcement news or press releases in FACTIVA[14] database. Information about merger participants' asset size is obtained from FDIC's statistics on depository institutions' fourth-quarter financial data report.

Finally, I gather tract-level demographic characteristics from the 2000 U.S. census. The rest of the 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 fintech. 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].

[Figure 2 about here.]

Finally, to distinguish between shadow banks and fintech, 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 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, as in Jagtiani et al. (2019), I classify as fintech two institutions that started reporting HMDA data in 2016 based on their growing volume and media recognition as the best online mortgage providers. These institutions were not classified as fintech by Buchak et al. (2018) and Fuster et al. (2019) because these focused on earlier years and larger lenders. The list of included institutions is the following: AmeriSave Mortgage, Better Mortgage, CashCall Inc.,

[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.

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 the mortgage supply of the different lender types. Estimating this relationship poses an empirical challenge: factors related to branch closings that are also associated with local economic characteristics that can correlate with mortgage lending and fintech adoption. For example, branch closings tend to occur in bank low profitability areas. 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 plausibly exogenous variation in the incidence of branch closings that follows a bank merger. Bank mergers tend to be followed by a period when the resulting merged institution engages in branch closings. These closings tend to be focused on areas in which the two preceding branch networks overlap. This both (i) increases the probability of branch closings in those areas and (ii) decreases the likelihood that the decision to close a branch is based on local economic characteristics.

The key 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 an exposed than in a control tract. This assumption will not hold if the decision to merge is made because of specific tract characteristics of tracts in which branch networks overlap. For instance, if particular 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 choices regarding the specific branches to close are 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 threaten the identification strategy's external validity. 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 size 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 increased market power, the generation of complementary business, or expansion into new markets. Although cost savings derived from consolidation may also be considered. It is doubtful 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 before the merger is only 1.4 percent (3.5 percent). Therefore, it is improbable that potential gains or savings in those tracts motivate the decision to merge.

Another 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 bring evidence against this possibility, in figure 3 I plot the annual number of fintech mortgages for all census tracts in my sample. The plot shows that fintech mortgages only significantly increase for all tracts of all mergers in my sample after the second post-merger year. Therefore the threat of reverse causation does not seem to represent a problem in this study since fintech mortgage levels in all tracts for all pre-merger and merger approval years are zero and could not drive the decision to merge.

[Figure 3 about here.]

I list sample mergers in Table 2. Included mergers are mergers that were approved during the 2000s (but before the financial crisis)[17], in which the two participating institutions had two 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) pre-merger assets, has 2,554 branches (723), and operates in 15 different states (9), while the median for all US banks is $302 million, four branches, and one state of operation, respectively.

[17] 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 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). And 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 pre-merger 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, a higher percentage of population below the poverty level, a lower median family income, fewer 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, pre-merger, and post-merger. I also allow for time-varying trends based on pre-merger 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:

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

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

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 $m$; $\sigma_t$ 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 the minority population, percentage of college-educated population, median family income, percentage of population 65 years old and over, percentage of rural population, 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 $\delta_{Post}$ 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 $Expose_{tcm}$; $\alpha_t$ 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.

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:

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

where $y_{iclmy}$ is an outcome for tract $t$, county $c$, of merger $m$ in year $y$, by lender type $l$,; $D^\tau_{my}$ is a dummy equal to 1 if year $y$ is $\tau$ years after merger $m$ is approved by federal regulators; and all other variables as previously defined. The range of $\tau$ is between $-8$ and 12. Standard errors are clustered at the county level. Finally, coefficient $\delta_\tau$ measures the difference, conditional on controls, in outcome $y$ between exposed and control tracts, $\tau$ years before or after a merger.

# 5 Results

**First stage** Figure 4 shows that in the five years before a merger, exposed tracts are not more likely than control tracts to experience a branch closing. However, there was 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 the post-merger years in which we have a balanced panel (9 years post-merger), differences go back to zero 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 each sample tract is generally one, point estimates can be interpreted as the change in relative probability of closing in exposed tracts relative to control tracts $\tau$ years since the merger was approved. I find that the probability of 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 the 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 4 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 5. This figure shows that there is also no evidence of pre-trends. It also shows that the number of branches in exposed tracts relative to control tracts is lower until the third year after a merger approval. 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 significant decrease in the number of branches in exposed relative to control tracts between the first and third post-merger years, which ranges between 0.24 and 0.38 branches. In the years that follow, the coefficients remain negative, although the statistical significance is lost.

[Figure 5 about here.]

**Intention to treat effects** I then focus on the reduced form intention-to-treat effect of the exposure to post-merger branch consolidation. In table 6 I estimate equation 3 for the number of mortgages 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 that shows lending in thousands of U.S. dollars. Here the negative reduced form effect for banks in dollar volume in the same period 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 an 11% decrease with respect to the total mortgages dollar volume baseline.

**Local average treatment effects** To identify the local average treatment effect of bank branch closings on mortgage lending, the main goal of this study, 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 nine years following a closure, 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 also translates 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 nine-year period. Compared to the annual bank mortgages baseline, the variation in the number of mortgages corresponds to a 44% decrease for banks and an 8% increase for fintech. 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 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:

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

Columns 1 and 3 respectively show that the average closing is associated with a significant reduction in bank mortgages and a significant increase in fintech mortgages. Specifically, after a closing, bank mortgages experience a significant accumulated decrease of 235 mortgages at the 90% level or above from the fourth year post-merger up until the eighth year. This reduction in bank lending represents a decrease of 69% with respect to the annual baseline mean for banks. Fintech mortgages experience a significant increase of 10 mortgages at the 90% level or above, after a closing in the third and fifth-year post-merger combined. These variations in lending for fintech represent an increase of 3% with respect to the annual baseline mean for banks (baseline mean for fintech 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 also have an impact on 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. These variations in lending represent 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 primarily reliant on relationship-intensive lending[18]. For banks, column 1 shows that lower median income tracts are 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 specific population segments. Bank borrowers, such as low-income individuals, who significantly benefit from a personal relationship 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 on fintech. Column 3 shows that the above-median income tracts drive the positive effect on 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 the 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 for these higher minority tracts. In turn, column 3 shows

[18] 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 on informal sources of credit.

that tracts with a higher white percentage of the population also 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 a relationship seems to carry a higher cost for minorities that both suffer a higher reduction of bank mortgages, do not benefit from 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 the female population. This analysis is consistent with findings that show that there is a gender gap in fintech lending[19]. In column 1, I show that both the effect of branch closings depresses more bank mortgages in tracts with a lower percentage of the female population and that precisely these tracts are the ones that are driving the effect of branch closures. Column 3 shows that tracts with a lower female share of the population are driving the increase of fintech mortgages after a closing. These two results suggest that males seem to be the ones driving both the decrease in 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 approaching 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 differ for the senior population. I test this subgroup of the population since people over 60 use less technology-intensive channels to access banking services[20] and this could influence the adoption of fintech that follows a closing. In column 1, I show that in tracts with a lower percentage of people 65 and over, the reduction in mortgages caused by a branch closing is much steeper and is driving the overall effect of closings. Moreover, this reduction in bank supply leads to credit rationing in these areas. This evidence 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 a less senior population also drive the increase in fintech mortgages that follow 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. These findings could be supportive evidence of the preferences of these groups for the less technology-intensive channels through which banking services have been traditionally provided.

**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 all

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

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 for population density, the percentage of the 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 a 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 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 a less rural population, and have more bank branches. This last point suggests that post-merger closings of bank branches are more focused on over-branched tracts. This focus on over-branched tracts, in turn, suggests that the estimated effects underestimate 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 nine-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 regulatory arbitrage. Since first, fintech lenders and not bank competitors are filling the gap left by the closure of a branch, and second, I compare 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 closings vary across population groups and that crucially, this leads to credit rationing for specific 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. In contrast, richer and lower minority areas are driving the rise 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 especially important for information-intensive borrowers such as low-income and minority groups. They are also supporting evidence for the view that fintech lenders are increasing the financial exclusion risk of specific segments of the population by using new machine learning methods and other new technologies.

The last takeaway of this paper is that branch closings are significantly changing mortgage markets. Even in the fintech era, where the financial industry makes intensive use of technology, bank branches are still vital for mortgage markets. This paper suggests that branches allow vulnerable to financial exclusion segments of the population to obtain credit by potentially reducing information asymmetries. The findings in this paper have important implications for the financial industry. It shows that most banks' branch network reduction tactic 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 U.S. are currently accelerating and are expected to continue in the following years. Simultaneously, the role of bank branches is being redefined. Branches are being transformed by reducing the emphasis on day-to-day operations and emphasizing the tailored service and commercial focus. Additionally, the financial industry is experiencing other vital disruptions. Large corporations with a significant 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 crucial in the coming years. The final equilibrium resulting from the interplay between these forces shapes necessary outcomes for financial the financial industry and the lives of most American citizens.

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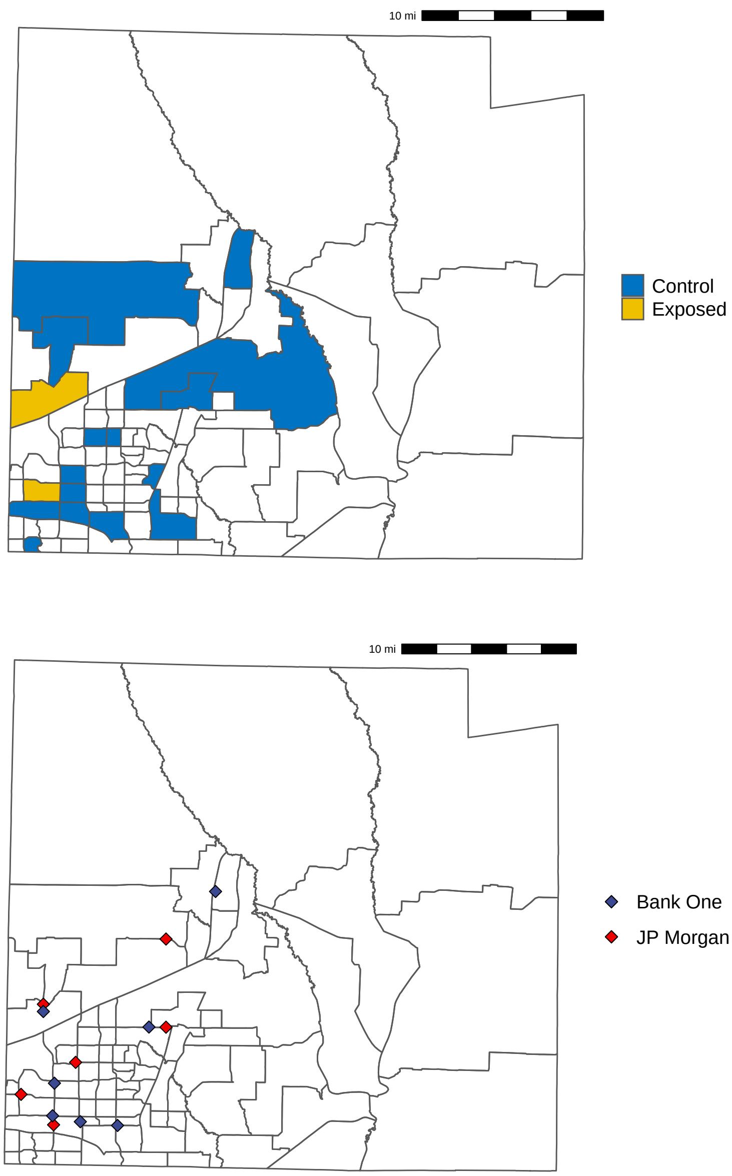
# 7 Figures

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

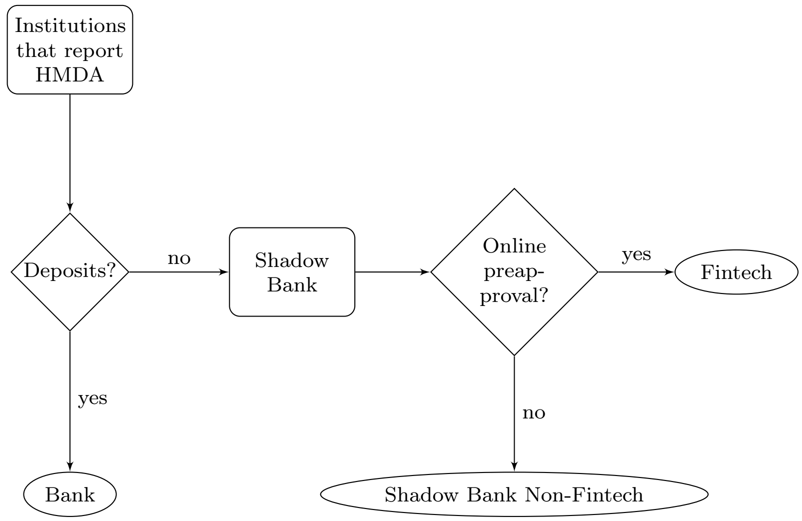
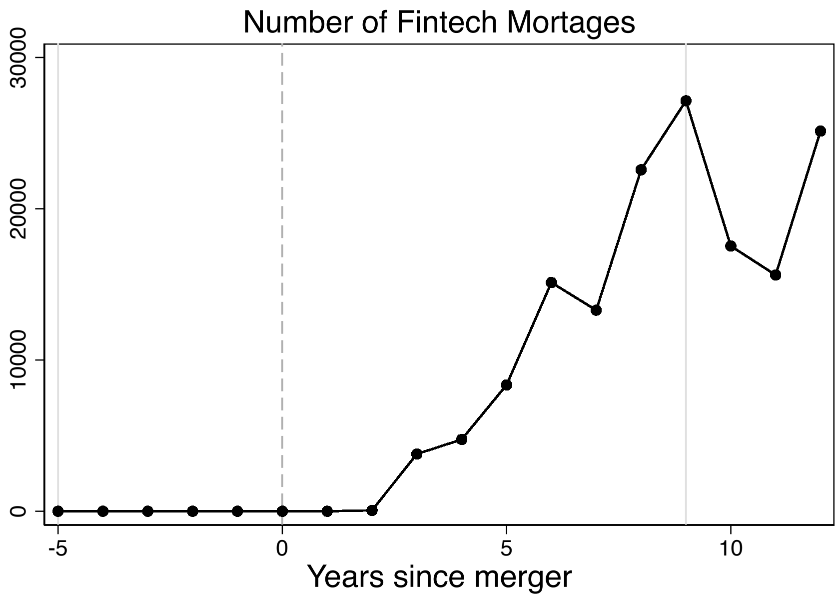
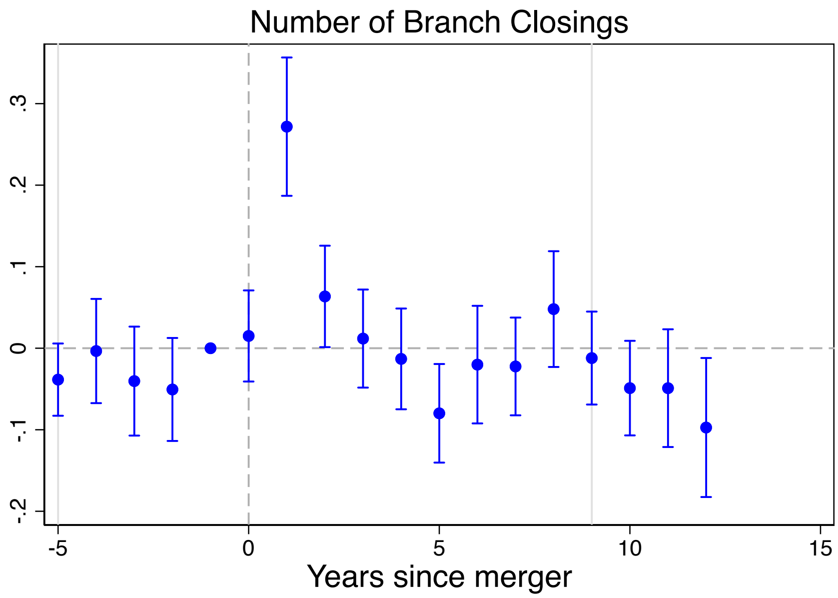


Figure 3: Number of Fintech Mortgages in Sample Tracts



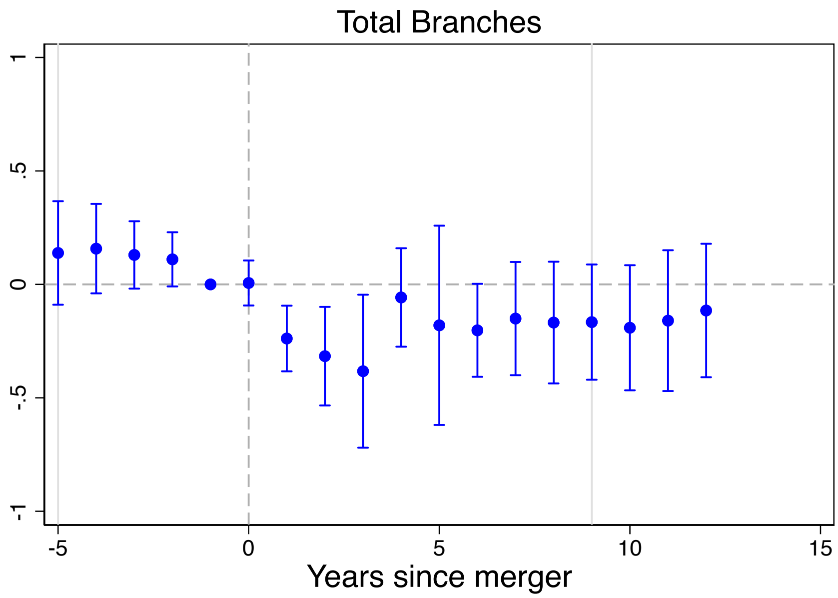

*Notes:* This figure plots the number of fintech mortgages in sample tracts for every year relative to the merger approval. $\tau = 0$ is the year the merger was approved by federal regulators.

Figure 4: 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 5: Exposure to Consolidation and Bank Branch Levels




*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.

# 8 Tables

Table 1: Sample Fintech Lenders

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

| Panel A: Buyer | | | |
|---|---|---|---|
| | Median | Min | Max |
| Total assets ($bn) | 565 | 81 | 1,200 |
| Branches | 2,554 | 594 | 5,723 |
| States of operation | 15 | 4 | 31 |
| Counties of operation | 401 | 47 | 698 |
| **Panel B: Target** | | | |
| | Median | Min | Max |
| Total assets ($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) |
| $\delta_0$ | 0.015 | 0.009 |
| | (0.028) | (0.050) |
| $\delta_1$ | 0.271*** | -0.236*** |
| | (0.043) | (0.074) |
| $\delta_2$ | 0.063** | -0.314*** |
| | (0.031) | (0.109) |
| $\delta_3$ | 0.011 | -0.381** |
| | (0.030) | (0.171) |
| $\delta_4$ | -0.014 | -0.056 |
| | (0.031) | (0.110) |
| $\delta_5$ | -0.081*** | -0.178 |
| | (0.031) | (0.223) |
| $\delta_6$ | -0.021 | -0.200* |
| | (0.036) | (0.104) |
| $\delta_7$ | -0.023 | -0.148 |
| | (0.030) | (0.126) |
| $\delta_8$ | 0.047 | -0.165 |
| | (0.036) | (0.136) |
| $\delta_9$ | -0.013 | -0.165 |
| | (0.029) | (0.128) |
| $\delta_{>9}$ | -0.061** | -0.165 |
| | (0.026) | (0.138) |
| Tract FEs | Yes | Yes |
| County × 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) |
| $\delta_0$ | 4.281 | -0.900 | -0.0728 | 3.308 |
| | (4.903) | (2.489) | (0.151) | (6.932) |
| $\delta_1$ | 4.727 | 5.004 | -0.0385 | 9.693 |
| | (7.779) | (5.225) | (0.148) | (12.48) |
| $\delta_2$ | 2.276 | 4.172 | -0.0261 | 6.421 |
| | (9.347) | (5.720) | (0.154) | (14.15) |
| $\delta_3$ | -4.428 | -2.024 | 0.917 | -5.535 |
| | (7.143) | (3.097) | (0.610) | (10.01) |
| $\delta_4$ | -10.60* | -3.244 | 0.602 | -13.24 |
| | (6.049) | (3.234) | (0.429) | (9.001) |
| $\delta_5$ | -11.00** | -2.216 | 1.494 | -11.72 |
| | (5.547) | (3.929) | (0.909) | (9.002) |
| $\delta_6$ | -9.160* | -3.232 | 0.240 | -12.15 |
| | (5.212) | (3.119) | (0.369) | (7.906) |
| $\delta_7$ | -9.140* | -2.666 | 0.604* | -11.20 |
| | (4.881) | (3.072) | (0.329) | (7.384) |
| $\delta_8$ | -7.482 | -1.379 | 0.665 | -8.196 |
| | (4.522) | (3.137) | (0.578) | (6.823) |
| $\delta_9$ | -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) |
| $\delta_0$ | 1,336.8 | 1.1 | -7.1 | 1,330.8 |
| | (1,253.2) | (456.3) | (37.2) | (1,530.4) |
| $\delta_1$ | 934.1 | 1,025.6 | 1.4 | 1,961.1 |
| | (2,237.4) | (1,031.5) | (36.3) | (3,112.6) |
| $\delta_2$ | 1,821.3 | 1,154.5 | 5.8 | 2,981.6 |
| | (2,851.0) | (1,399.9) | (37.9) | (3,988.4) |
| $\delta_3$ | -921.0 | -140.7 | 254.1 | -807.5 |
| | (2,301.6) | (713.7) | (168.9) | (2,951.4) |
| $\delta_4$ | -2,943.7** | -746.6 | 144.2 | -3,546.1* |
| | (1,474.8) | (570.5) | (120.4) | (1,955.0) |
| $\delta_5$ | -3,169.0** | -483.5 | 410.0 | -3,242.4 |
| | (1,526.0) | (793.9) | (252.4) | (2,089.5) |
| $\delta_6$ | -2,314.6* | -837.0 | 53.1 | -3,098.5* |
| | (1,342.8) | (518.0) | (110.8) | (1,651.7) |
| $\delta_7$ | -2,372.4** | -220.5 | 140.8 | -2,452.1* |
| | (1,161.2) | (529.8) | (87.5) | (1,478.3) |
| $\delta_8$ | -1,281.2 | -43.9 | 69.1 | -1,256.0 |
| | (1,196.0) | (734.8) | (131.6) | (1,647.2) |
| $\delta_9$ | -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 × Closing | -16.87* | 2.721 | 3.001*** | -11.15 |
| | (8.727) | (5.284) | (0.810) | (12.88) |
| 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 |
| $R^2$ | 0.42 | 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 | 901.59 | 640.50*** | -1,174.17 |
| | (2,487.45) | (1,236.08) | (222.10) | (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) |
| $\delta_0$ | 0.526 | -5.656 | 0.549 | -4.581 |
| | (23.14) | (13.98) | (2.142) | (34.14) |
| $\delta_1$ | 1.544 | 11.82 | 0.953 | 14.31 |
| | (21.12) | (12.76) | (1.955) | (31.15) |
| $\delta_2$ | -7.782 | 8.574 | 1.079 | 1.871 |
| | (23.00) | (13.90) | (2.130) | (33.94) |
| $\delta_3$ | -29.02 | -9.242 | 4.222* | -34.04 |
| | (23.42) | (14.15) | (2.169) | (34.56) |
| $\delta_4$ | -48.83** | -13.30 | 3.032 | -59.09* |
| | (23.62) | (14.27) | (2.187) | (34.85) |
| $\delta_5$ | -52.12** | -11.48 | 6.136*** | -57.46 |
| | (23.76) | (14.36) | (2.200) | (35.05) |
| $\delta_6$ | -47.94** | -14.85 | 2.231 | -60.56* |
| | (23.80) | (14.38) | (2.203) | (35.11) |
| $\delta_7$ | -47.67** | -12.47 | 3.526 | -56.62 |
| | (23.80) | (14.38) | (2.204) | (35.12) |
| $\delta_8$ | -41.34* | -8.868 | 3.363 | -46.85 |
| | (23.73) | (14.34) | (2.198) | (35.02) |
| $\delta_9$ | -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) |
| $\delta_0$ | 785.4 | -105.0 | 143.1 | 823.6 |
| | (6,595.0) | (3,270.4) | (587.3) | (8,905.5) |
| $\delta_1$ | -564.0 | 2,817.6 | 245.7 | 2,499.4 |
| | (6,018.8) | (2,984.7) | (536.0) | (8,127.5) |
| $\delta_2$ | 1,721.9 | 3,082.0 | 275.1 | 5,079.1 |
| | (6,556.1) | (3,251.2) | (583.8) | (8,853.1) |
| $\delta_3$ | -7,003.2 | -668.8 | 1,104.7* | -6,567.3 |
| | (6,676.1) | (3,310.6) | (594.5) | (9,015.0) |
| $\delta_4$ | -13,018.7* | -2,543.2 | 697.5 | -14,864.4 |
| | (6,732.4) | (3,338.6) | (599.5) | (9,091.0) |
| $\delta_5$ | -14,415.8** | -1,889.1 | 1,601.5*** | -14,703.4 |
| | (6,771.4) | (3,357.9) | (603.0) | (9,143.7) |
| $\delta_6$ | -12,190.1* | -3,134.5 | 461.2 | -14,863.4 |
| | (6,782.6) | (3,363.5) | (604.0) | (9,158.9) |
| $\delta_7$ | -12,539.8* | -1,118.7 | 787.4 | -12,871.1 |
| | (6,784.4) | (3,364.4) | (604.2) | (9,161.3) |
| $\delta_8$ | -8,858.6 | -602.6 | 467.8 | -8,993.3 |
| | (6,764.9) | (3,354.7) | (602.4) | (9,135.0) |
| $\delta_9$ | -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 × 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 (1) | Shadow banks (2) | Fintechs (3) | Total (4) | Observations (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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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# Appendices

## A Background

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

| Variable | (1)<br>Exposed | (2)<br>All other | (3)<br>$p$-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. 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.