

# Fintech, Bank Branch Closings, and Mortgage Markets \*

Josep Gisbert<sup>†</sup>

IE Business School and IE University

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## Abstract

This paper studies whether bank branch closures affect fintech mortgage lending in the U.S. using data for the 1999–2016 period. My identification exploits granular 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%. The results show a strong substitution pattern and are driven by wealthier areas and areas with relatively smaller populations of women, seniors, and minorities.

Keywords: *fintech, branch closings, digital banking, financial inclusion, sustainable finance*

JEL Classification: D14, G21, G23, G51

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<sup>†</sup>IE Business School and IE University. E-mail: josep.gisbert@ie.edu

# 1 Introduction

Do fintech firms substitute banks as mortgage lenders after a branch closing? Do fintech firms facilitate the financial inclusion of traditionally vulnerable population segments after a branch closing? In this paper, I answer these questions using granular data for the 1999–2016 period. To my knowledge, this is the first study about the effect of bank branch closings on fintech mortgage adoption and their impact on financial inclusion during the “fintech era”.

This paper focuses on the effects of two disruptions in the U.S. mortgage market since the Great Recession in 2007: (i) a continuous stream of bank branch closures and (ii) the emergence and consolidation of fintech companies as a new type of lender. Fintech companies are financial service providers that use technology extensively. Over the past two decades, fintech’s market share in the US mortgage market has grown rapidly, from zero in the mid-2000s to over 12% in the mid-2010s. In contrast, the number of bank branches has significantly reduced, with 10,631 closures between 2008 and 2020. This represents a 12% overall decrease from the pre-recession peak. As a laboratory for my analysis, I use the U.S. mortgage market, a \$11.05 trillion market critical for the stability of the overall U.S. financial system.

My results show that branch closings persistently increase local mortgage fintech adoption. The cumulative increase in fintech mortgages over the nine years following a closing relative to control tracts is 27 mortgages or 8% of a baseline of 340 bank mortgages in the pre-merger year. Conversely, branch closings lead to a significant decrease in bank mortgage supply. The cumulative reduction in bank mortgages relative to control tracts over the nine years following a closing is 152 mortgages or 44% of the annual bank baseline. These results show a strong substitution pattern between bank credit and fintech credit. This substitution is driven by wealthier areas and areas with relatively smaller populations of women, seniors, and minorities. My results show that areas with larger, traditionally vulnerable segments of the population, such as poor individuals and minorities, suffer credit rationing due to branch closings. This credit rationing is explained by a reduction in bank credit and the focus of fintech companies on other areas with less vulnerable borrower profiles.

To study the effect of branch closures 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, and it captures 90 percent of lending activity measured by loan volume. Studying the effect of branch closures on local mortgage markets poses an empirical challenge. Banks tend to close branches in areas with low current or expected profitability. Since profitability is also related to tract characteristics that also affect mortgage credit, a simple study comparing areas where a branch closes and those where there is no closing will produce a biased estimate

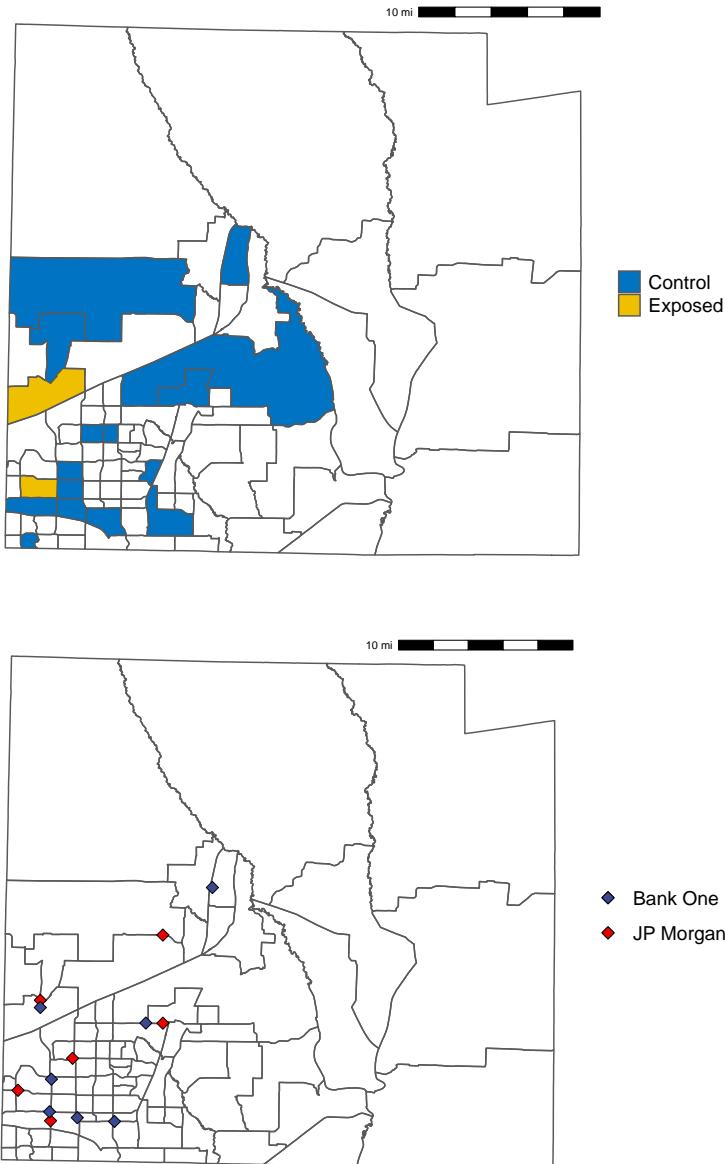
of the effects of branch closures. To overcome this problem, I use an instrument based on within-county, tract-level variation in exposure to post-merger branch consolidation, an empirical approach pioneered by [Nguyen \(2019\)](#).

The instrument exploits closures due to the merger of two large national banks that operate branches in close geographical proximity. Figure 1 illustrates this identification strategy for a sample merger and county. This framework compares the pre-merger and post-merger level of lending in exposed tracts, which had branches from both merging banks before 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 characteristics that determine credit. To warrant this, my sample only includes mergers between very large banks. Banks that in pre-merger assets had at least \$50 billion, 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. Finally, to evaluate the effects of closures on fintech lenders, I classify all institutions that report HMDA data into three types: banks, shadow banks non-fintech, or fintech using established methods in the literature (See: [Buchak et al. 2018](#); [Fuster et al. 2019](#); [Jagtiani et al. 2019](#)).

My research yields new insights into the effects of bank branch closures on both mortgage supply and financial inclusion. While previous research by [Nguyen \(2019\)](#), found that bank branch closures do not affect local mortgage supply in the U.S., that work did not focus on the role of shadow banks. In contrast, by analyzing the role of fintech companies and the rest of the shadow banks, my analysis shows that the previous null result conceals two significant changes in the U.S. mortgage market. First, branch closings cause a strong substitution within the lender mix that provides local mortgage supply. This change in the lenders' mix occurs between banks, who reduce their mortgage supply, to fintech, which increases it. Second, this change in the lender mix caused by closings is not neutral for traditionally vulnerable population segments. Since fintech lenders issue mortgages to a different profile of borrowers than banks do, the resulting public that obtains, and crucially those that no longer have access to credit, varies.

The closure of branches results in credit rationing for regions with a higher concentration of information-intensive borrowers, including minorities and low-income individuals. Fintech companies, by focusing on areas with more prosperous and less diverse populations, do not help overcome the credit rationing caused by banks and contribute to the financial exclusion of vulnerable population segments. My findings align with those of [Avramidis et al. \(2022\)](#),

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, which was approved in 2004. The map on the bottom shows the network of the merger banks in the year before merger approval.

who found that merger-induced bank branch closings increase marketplace loan requests and loan acceptance rates for a peer-to-peer lender focused on personal loans: Lending Club. However, my results focus on the mortgage market rather than the personal loan market. Cover the nine largest fintech firms in the market object of my study, rather than a single one. And I do not focus exclusively on the effects of closings on bank credit supply as I measure the impact of closings on all lender types of local mortgage supply: banks, fintech companies, and the rest of the shadow banks.

My work also contributes to the debate about the origin of fintech growth in credit markets. Some papers support the view that fintech growth is driven by regulatory arbitrage ([Irani et al. 2020](#); [de Roure et al. 2021](#)), while others document that new technology and improved methods could be its primary explanation ([Buchak et al. 2018](#); [Fuster et al. 2019](#)). Here, I make granular comparisons and show that after a branch closes, fintech lenders, and not other banks, are the ones that capture the “deserted” borrowers. My findings suggest that fintech lenders provide differentiated products and prices, employ differential technology, and do not base their growth exclusively on regulatory arbitrage.

Taken together, this paper’s findings highlight the critical role of bank branches, which, even in this “fintech era” characterized by the intensive use of technology and new channels to reach customers, still fulfill an essential role in transmitting soft information. My results show that the branch’s role of facilitating bank-branch-borrower relationships and transmitting soft information is vital for household credit outcomes despite new technological advancements in the mortgage market.

My findings have two implications for policy. Branch closures have fostered the substitution of more strictly regulated banks for less tightly regulated institutions: fintech and the rest of shadow banks. This change in the lender mix may threaten the system’s financial stability, and this change should warrant the close attention of regulators. Secondly, the rising footprint of shadow banks has led to a shift from relationship lending to transaction lending. This has damaged borrowers’ access to credit, as [Aldasoro et al. \(2023\)](#) also have documented. Policymakers should implement measures to protect information-intensive borrowers and improve their financial inclusion, especially after a wave of branch closures. Although fintech companies partly fill the gap left by banks after a branch closure, they supply credit to areas with more affluent, non-minority, younger, and male individuals, leaving other areas with population groups that lost their bank-branch-borrower relationship suffering the brunt of the decrease in credit.

## 2 Data

All sources of data in 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<sup>1</sup>, therefore, their size varies depending on their population density. After each census, the borders of some tracts are slightly updated<sup>2</sup>. In

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<sup>1</sup>With a minimum of 1,200 inhabitants and a maximum of 8,000.

<sup>2</sup>Census tracts are split, merged, or untouched, depending on population change, and minor boundary corrections are sometimes allowed as well.

this paper, I use 2000 census borders<sup>3</sup>.

To analyze the impact of branch closings on local lending, I obtained 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<sup>4</sup>. 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<sup>5</sup>. HMDA data are at the loan application level and include information about the census tract in which the borrower is located<sup>6</sup>, the amount of the application, whether the mortgage has been approved or denied, the 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 from 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 institutions insured by the Federal Deposit Insurance Corporation (FDIC). The listing is 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.

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<sup>3</sup>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.

<sup>4</sup>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.

<sup>5</sup>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. For-profit mortgage-lending institutions other than banks, savings associations, or credit unions are subject to HMDA regulation if the institution has 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.

<sup>6</sup>Not based in the location of the lending financial institution.

branches of foreign banks. All institutions with branch offices must submit the survey; only institutions with one main office are exempt. Apart from the branch deposit information, the SOD contains data on 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 with GPS coordinates available in the SOD. For branches whose GPS coordinates are unavailable, 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 was 1.7% and declined 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. I use the same method as for the bank branch’s location to locate the branch closings. The percentage of non-located branch closings for the period of interest is 2.4%. The percentage of unmapped observations in 1999 was 5.9% and declined 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 1999–2020 period<sup>7</sup>. 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<sup>8</sup> database. Information about merger participants’ asset size is obtained from FDIC’s statistics on depository institutions’ fourth-quarter financial data reports.

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 Fintech 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<sup>9</sup>. Second, following [Buchak et al. \(2018\)](#) institution classification

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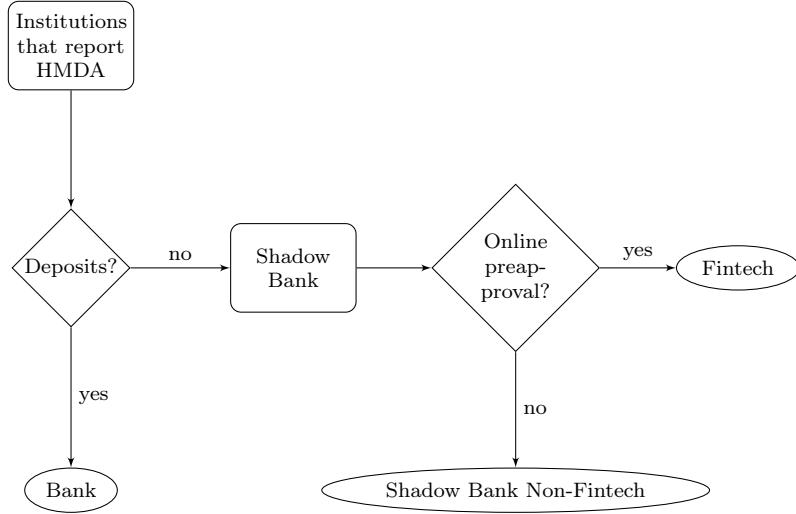
<sup>7</sup>Since approval dates are always later than the effective dates, I look for the period 1999–2020

<sup>8</sup>Global news database of more than 33,000 sources owned by Dow Jones & Company.

<sup>9</sup>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

methodology, I classify as banks all depository institutions, and as shadow banks the rest of institutions<sup>10</sup>.

Figure 2: Fintech Classification Method



*Notes:* This process flow diagram shows the fintech classification method. First, all institutions that report HMDA data are classified as banks or shadow banks based on whether they are depository institutions. Second, shadow banks are classified as fintech starting the year in which they have an online mortgage preapproval system in place that requires no human intervention from the lender side. If they never do they are always classified as shadow bank non-fintech.

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., Everett Financial, Guaranteed Rate, loanDepot, Movement Mortgage, SoFi, and Quicken. An illustration of this classification method is displayed in figure 2, and a summary of fintech listings in the three cited papers is shown in table 1.

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<sup>10</sup>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.

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).

## 4 Empirical Strategy

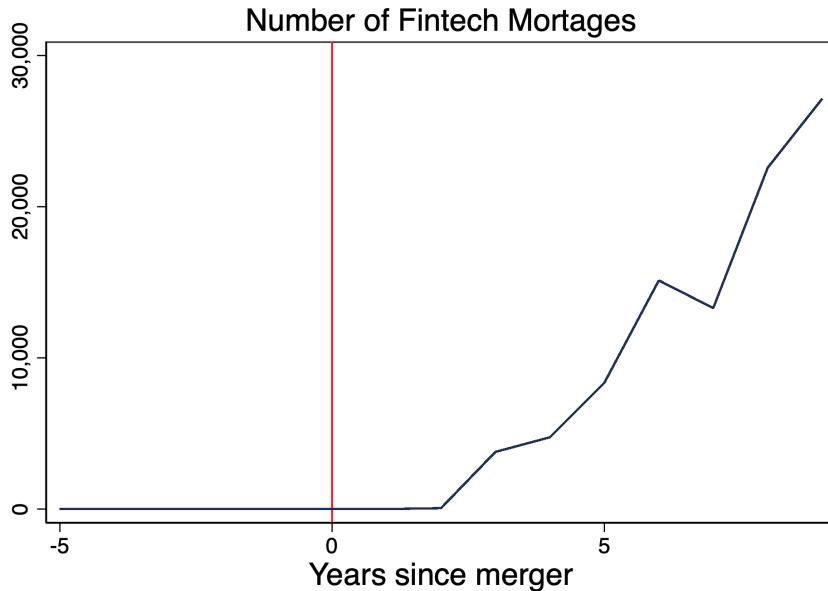
**Empirical challenge** The relationship of interest is the effect of branch closings on the mortgage supply of the different lender types. Estimating this relationship poses an empirical challenge: factors related to branch closings that are also associated with local economic characteristics that can 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 focus 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.

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. Year = 0 is the year federal regulators approved the merger. Only the years for which the panel is balanced are displayed.

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 threaten the instrument's internal validity. 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 will further discuss external validity later 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 have at least \$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.

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.

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 billion, the author estimated that the median percentage of the buyer (target) banks' deposits held 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 likely 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.

I list sample mergers in Table 2. Included mergers are mergers that were approved during the 2000s (but before the financial crisis)<sup>11</sup>, in which the two participating institutions had two or more branches, had \$50 billion in pre-merger assets and had overlapping networks in at least one census tract.

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.

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

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<sup>11</sup>Mergers occurred in 2008 and later years were excluded from the sample

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.

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.

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-differences (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:

$$Mortgage_{tcm} = \sigma_t + (\mu_y \times \nu_c) + \mathbf{X}_t \lambda_y + \rho_{Post}(\overline{Post}_{my} \times \overline{Closing}_{tcm}) + \eta_{tcm} \quad (1)$$

$$(\overline{Post}_{my} \times \overline{Closing}_{tcm}) = \alpha_t + (\gamma_y \times \kappa_c) + \mathbf{X}_t \beta_y + \delta_{Post}(\overline{Post}_{my} \times \overline{Expose}_{tcm}) + \epsilon_{tcm} \quad (2)$$

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-differences 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:

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

where  $y_{tcmyl}$  is an outcome for tract  $t$ , county  $c$ , of merger  $m$  in year  $y$ , by lender type  $l$ ;  $D_{my}^\tau$  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.

Table 4: Tract Summary Statistics: Exposed vs. Control

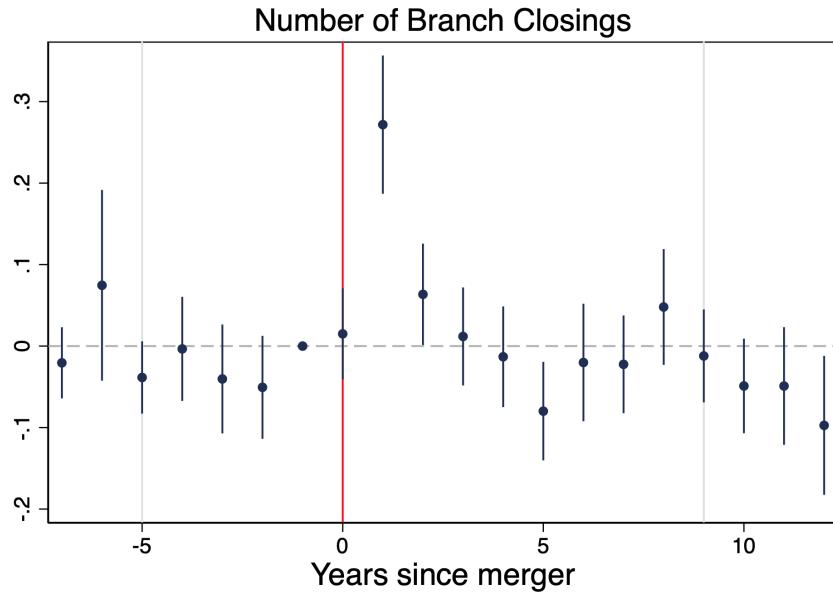
Variable	(1) Exposed	(2) Control	(3) <i>p</i> -value on difference
Population	5,752 [3,766]	5,539 [2,872]	0.519
Population density	2,498 [3,544]	6,309 [17,296]	0.290
Percent minority	28.1 [23.2]	29.3 [23.7]	0.935
Percent college educated	59.1 [19.1]	60.9 [18.6]	0.034
Percent poverty level	13.3 [11.6]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

## 5 Results

**First stage** Figure 4 shows that in the five pre-merger years for which we have a balanced panel, 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: Exposure to Consolidation and Bank Branch Closings

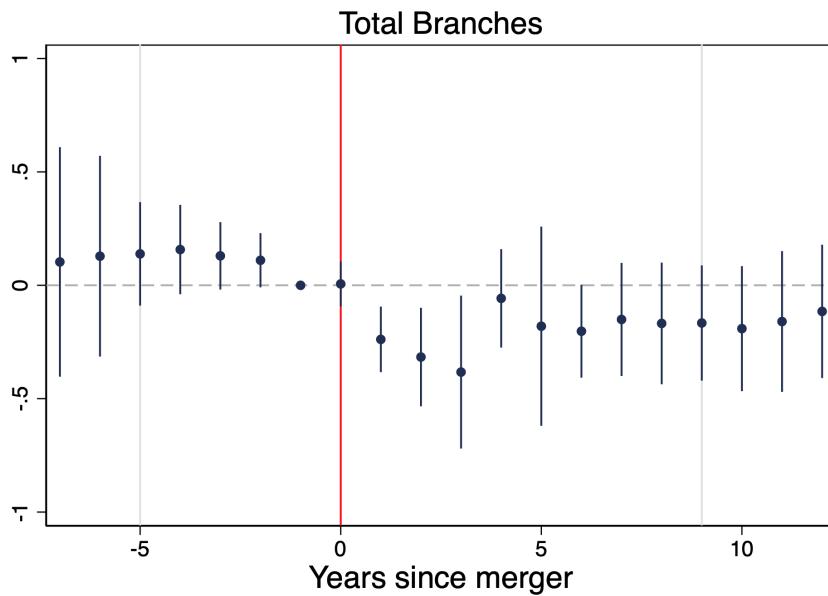


*Notes:* This figure plots the first-stage relationship between exposure to consolidation and the incidence of branch closings, obtained from estimating equation 3. The bars show 95 percent confidence intervals,  $\tau = 0$  is the year the merger was approved by federal regulators, and all coefficients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

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: 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.

**Intention-to-treat effects** I then focus on the reduced form intention-to-treat effect of the exposure to post-merger branch consolidation on mortgage lending. 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

Table 5: First Stage Estimates

	(1) Number branch closings	(2) Total branches
$\delta_{<-1}$	-0.024 (0.021)	0.124 (0.092)
$\delta_0$	0.015 (0.028)	0.009 (0.050)
$\delta_1$	0.271*** (0.043)	-0.236*** (0.074)
$\delta_2$	0.063** (0.031)	-0.314*** (0.109)
$\delta_3$	0.011 (0.030)	-0.381** (0.171)
$\delta_4$	-0.014 (0.031)	-0.056 (0.110)
$\delta_5$	-0.081*** (0.031)	-0.178 (0.223)
$\delta_6$	-0.021 (0.036)	-0.200* (0.104)
$\delta_7$	-0.023 (0.030)	-0.148 (0.126)
$\delta_8$	0.047 (0.036)	-0.165 (0.136)
$\delta_9$	-0.013 (0.029)	-0.165 (0.128)
$\delta_{>9}$	-0.061** (0.026)	-0.165 (0.138)
Tract FEs	Yes	Yes
County $\times$ Year FEs	Yes	Yes
Observations	42,462	42,462
R <sup>2</sup>	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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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.

Table 6: Reduced Form Estimates

	Reduced Form			
	(1) Bank Mortgages	(2) Shadow bank Mortgages	(3) Fintech Mortgages	(4) Total Mortgages
$\delta_{<-1}$	-2.426 (6.942)	-1.406 (2.445)	-0.333 (0.209)	-4.164 (8.995)
$\delta_0$	4.281 (4.903)	-0.900 (2.489)	-0.0728 (0.151)	3.308 (6.932)
$\delta_1$	4.727 (7.779)	5.004 (5.225)	-0.0385 (0.148)	9.693 (12.48)
$\delta_2$	2.276 (9.347)	4.172 (5.720)	-0.0261 (0.154)	6.421 (14.15)
$\delta_3$	-4.428 (7.143)	-2.024 (3.097)	0.917 (0.610)	-5.535 (10.01)
$\delta_4$	-10.60* (6.049)	-3.244 (3.234)	0.602 (0.429)	-13.24 (9.001)
$\delta_5$	-11.00** (5.547)	-2.216 (3.929)	1.494 (0.909)	-11.72 (9.002)
$\delta_6$	-9.160* (5.212)	-3.232 (3.119)	0.240 (0.369)	-12.15 (7.906)
$\delta_7$	-9.140* (4.881)	-2.666 (3.072)	0.604* (0.329)	-11.20 (7.384)
$\delta_8$	-7.482 (4.522)	-1.379 (3.137)	0.665 (0.578)	-8.196 (6.823)
$\delta_9$	-5.170 (4.943)	1.071 (3.524)	0.565 (0.495)	-3.534 (7.905)
$\delta_{>9}$	-2.111 (8.936)	0.0906 (3.514)	0.259 (0.854)	-1.762 (11.07)
Tract FEs	Yes	Yes	Yes	Yes
County $\times$ Year FEs	Yes	Yes	Yes	Yes
Observations	42,462	42,462	42,462	42,462
R <sup>2</sup>	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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**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 equa-

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 (1,682.4)	-202.6 (511.8)	-76.0 (57.5)	-1,486.2 (2,106.4)
$\delta_0$	1,336.8 (1,253.2)	1.1 (456.3)	-7.1 (37.2)	1,330.8 (1,530.4)
$\delta_1$	934.1 (2,237.4)	1,025.6 (1,031.5)	1.4 (36.3)	1,961.1 (3,112.6)
$\delta_2$	1,821.3 (2,851.0)	1,154.5 (1,399.9)	5.8 (37.9)	2,981.6 (3,988.4)
$\delta_3$	-921.0 (2,301.6)	-140.7 (713.7)	254.1 (168.9)	-807.5 (2,951.4)
$\delta_4$	-2,943.7** (1,474.8)	-746.6 (570.5)	144.2 (120.4)	-3,546.1* (1,955.0)
$\delta_5$	-3,169.0** (1,526.0)	-483.5 (793.9)	410.0 (252.4)	-3,242.4 (2,089.5)
$\delta_6$	-2,314.6* (1,342.8)	-837.0 (518.0)	53.1 (110.8)	-3,098.5* (1,651.7)
$\delta_7$	-2,372.4** (1,161.2)	-220.5 (529.8)	140.8 (87.5)	-2,452.1* (1,478.3)
$\delta_8$	-1,281.2 (1,196.0)	-43.9 (734.8)	69.1 (131.6)	-1,256.0 (1,647.2)
$\delta_9$	-1,304.6 (1,210.7)	243.3 (881.9)	76.1 (118.8)	-985.2 (1,807.8)
$\delta_{>9}$	-846.2 (2,299.6)	420.2 (1,019.9)	3.5 (238.9)	-422.5 (2,896.5)
Tract FEs	Yes	Yes	Yes	Yes
County $\times$ Year FEs	Yes	Yes	Yes	Yes
Observations	42,462	42,462	42,462	42,462
R <sup>2</sup>	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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

tions 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 the number of 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.

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* (8.727)	2.721 (5.284)	3.001*** (0.810)	-11.15 (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 <sup>2</sup>	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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

To evaluate the effects of bank branch closings on mortgage lending for each lender type over time, in table 10, I estimate a more flexible version of the 2SLS equation 1:

$$Mortgage_{tcmyl} = \sigma_t + (\mu_y \times \nu_c) + \mathbf{X}_t \lambda_y + \delta_\tau (\widehat{D_{my}^\tau} \times \widehat{Closing_{tcm}}) + \eta_{tcmyl} \quad (4)$$

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

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 $\times$ 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 $\times$ 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 <sup>2</sup>	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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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 12 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-

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 (19.99)	-8.614 (12.08)	-0.679 (1.851)	-28.83 (29.48)
$\delta_0$	0.526 (23.14)	-5.656 (13.98)	0.549 (2.142)	-4.581 (34.14)
$\delta_1$	1.544 (21.12)	11.82 (12.76)	0.953 (1.955)	14.31 (31.15)
$\delta_2$	-7.782 (23.00)	8.574 (13.90)	1.079 (2.130)	1.871 (33.94)
$\delta_3$	-29.02 (23.42)	-9.242 (14.15)	4.222* (2.169)	-34.04 (34.56)
$\delta_4$	-48.83** (23.62)	-13.30 (14.27)	3.032 (2.187)	-59.09* (34.85)
$\delta_5$	-52.12** (23.76)	-11.48 (14.36)	6.136*** (2.200)	-57.46 (35.05)
$\delta_6$	-47.94** (23.80)	-14.85 (14.38)	2.231 (2.203)	-60.56* (35.11)
$\delta_7$	-47.67** (23.80)	-12.47 (14.38)	3.526 (2.204)	-56.62 (35.12)
$\delta_8$	-41.34* (23.73)	-8.868 (14.34)	3.363 (2.198)	-46.85 (35.02)
$\delta_9$	-33.81 (23.68)	-1.108 (14.31)	3.067 (2.192)	-31.85 (34.93)
$\delta_{>9}$	-23.38 (21.23)	-3.537 (12.83)	2.061 (1.966)	-24.86 (31.32)
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 <sup>2</sup>	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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

income and minority buyers are primarily reliant on relationship-intensive lending<sup>12</sup>. For

<sup>12</sup>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)

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 (5,696.2)	-1,109.5 (2,824.7)	-171.9 (507.3)	-8,809.1 (7,691.8)
$\delta_0$	785.4 (6,595.0)	-105.0 (3,270.4)	143.1 (587.3)	823.6 (8,905.5)
$\delta_1$	-564.0 (6,018.8)	2,817.6 (2,984.7)	245.7 (536.0)	2,499.4 (8,127.5)
$\delta_2$	1,721.9 (6,556.1)	3,082.0 (3,251.2)	275.1 (583.8)	5,079.1 (8,853.1)
$\delta_3$	-7,003.2 (6,676.1)	-668.8 (3,310.6)	1,104.7* (594.5)	-6,567.3 (9,015.0)
$\delta_4$	-13,018.7* (6,732.4)	-2,543.2 (3,338.6)	697.5 (599.5)	-14,864.4 (9,091.0)
$\delta_5$	-14,415.8** (6,771.4)	-1,889.1 (3,357.9)	1,601.5*** (603.0)	-14,703.4 (9,143.7)
$\delta_6$	-12,190.1* (6,782.6)	-3,134.5 (3,363.5)	461.2 (604.0)	-14,863.4 (9,158.9)
$\delta_7$	-12,539.8* (6,784.4)	-1,118.7 (3,364.4)	787.4 (604.2)	-12,871.1 (9,161.3)
$\delta_8$	-8,858.6 (6,764.9)	-602.6 (3,354.7)	467.8 (602.4)	-8,993.3 (9,135.0)
$\delta_9$	-8,834.7 (6,748.0)	445.6 (3,346.3)	487.7 (600.9)	-7,901.4 (9,112.1)
$\delta_{>9}$	-7,008.1 (6,051.3)	982.3 (3,000.8)	250.2 (538.9)	-5,775.6 (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 <sup>2</sup>	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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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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.

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 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<sup>13</sup>. 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

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<sup>13</sup>Chen et al. (2021) show that while 29% of men use fintech products and services, only 21% of women do.

Table 12: Second Stage Splits: Demographic

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

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: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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<sup>14</sup> 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 13 and compare columns 2 and 3 to column 1. Merger sample tracts are more similar to tracts with bank branch closings than all branched tracts in several dimensions. For instance, compared to all branched tracts, both sample, and closing tracts, have larger population, higher percentage of college-educated population, lower share of population below the poverty level, lower share of rural population, higher 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.

To further scrutinize the LATE identified, I construct table 14. 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

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<sup>14</sup>Dodini et al. (2016) show that only 18% of people over the age of 60 use mobile banking.

Table 13: Representativeness of the Merger Sample

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

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 hold. 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 14 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 lower share of rural population, and have a higher number of 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 14: 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.

## 6 Conclusion

The main contribution of this paper is to show that bank branch closings significantly change the lender mix of the mortgage market and the financial inclusion of large groups of the population. Although closings do not affect the overall supply of mortgages in the market, this fact obscures an important change for mortgage markets. I show that closings 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. 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 population segments. Poorer and higher minority areas both experience a more severe depression of bank credit and do not benefit from increased fintech credit after a branch closing. In contrast, more affluent 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. Bank-branch-customer relationships are essential for information-intensive borrowers such as low-income and minority groups. They are also supporting evidence that fintech lenders are increasing the financial exclusion risk of specific population segments 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 fosters 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 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 tailored service and commercial focus. The financial industry is experiencing other vital disruptions too. 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, industry newcomers, and bank branches' roles will still be crucial in the coming years. The final equilibrium resulting from the interplay between these forces shapes essential outcomes for the financial industry and the lives of most citizens.

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# Contents (Appendix)

<b>Appendices</b>	<b>2</b>
A Sample . . . . .	2
B Summary statistics . . . . .	12

# Appendices

## A Sample

Figure A1: Spatial variation in fintech mortgage originations market share 2008 and 2009

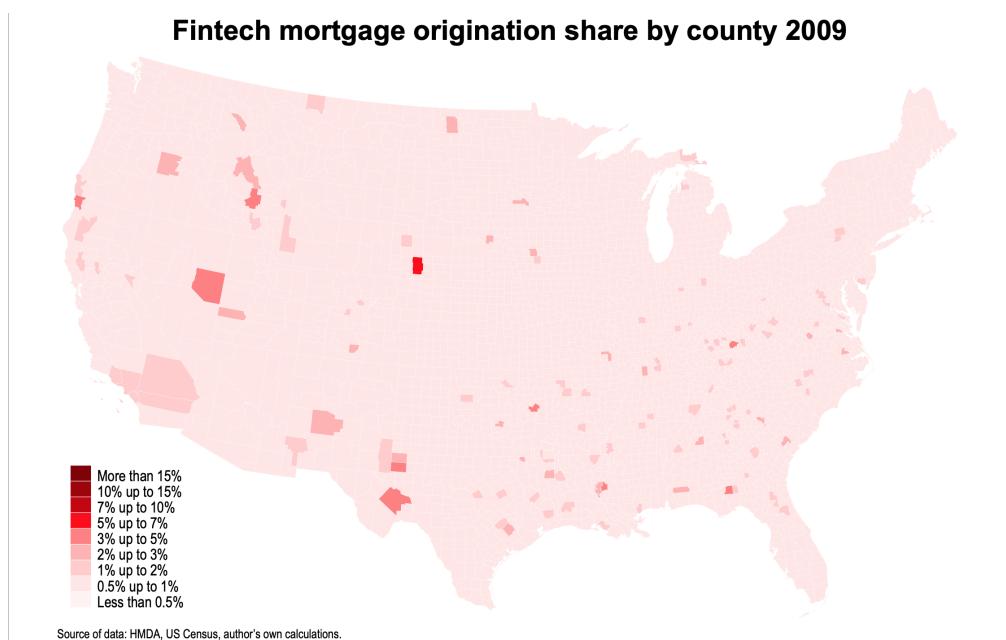
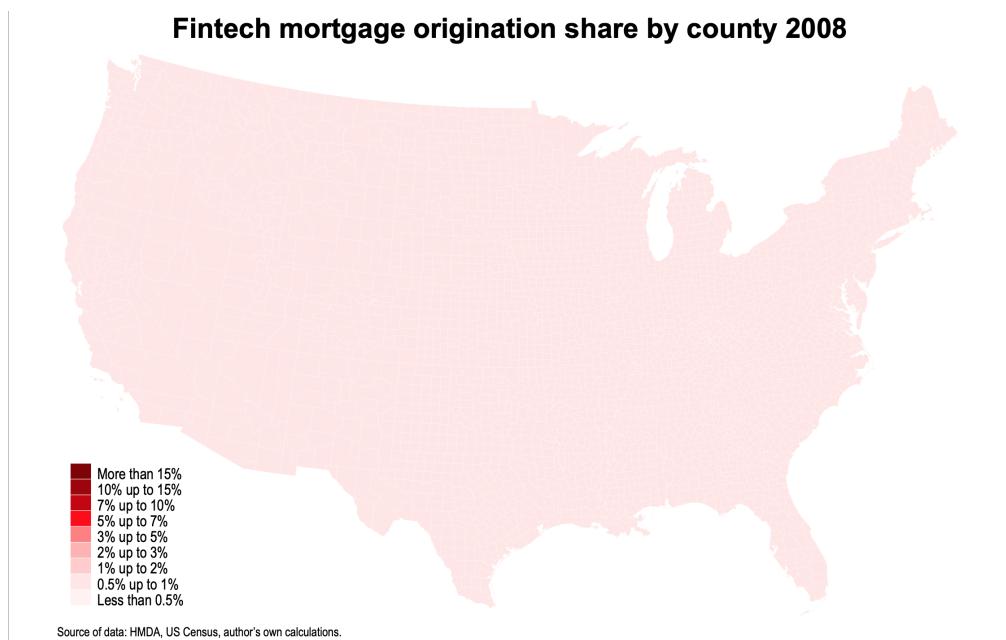


Figure A2: Spatial variation in fintech mortgage originations market share 2010 and 2011

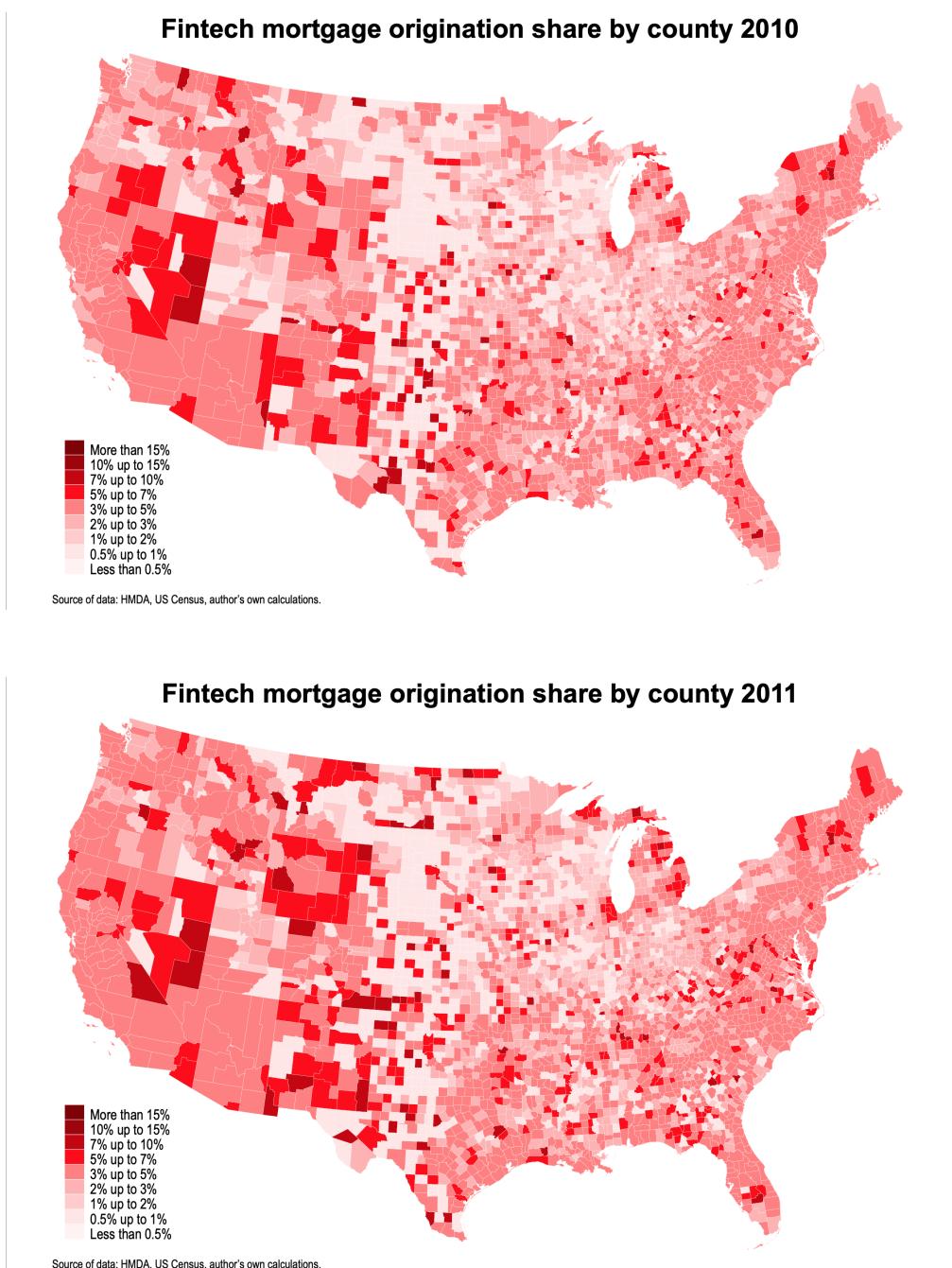


Figure A3: Spatial variation in fintech mortgage originations market share 2012 and 2013

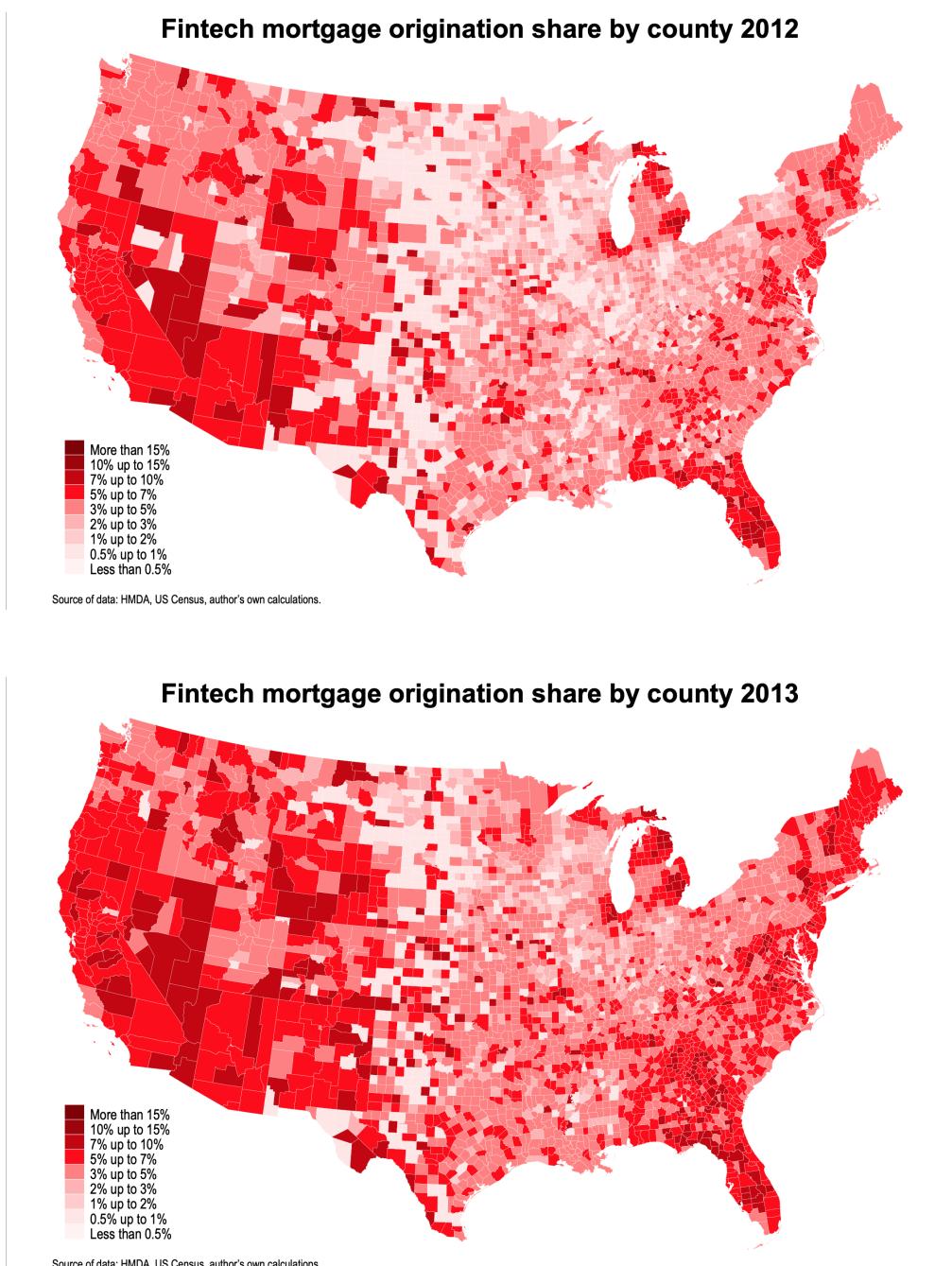


Figure A4: Spatial variation in fintech mortgage originations market share 2014 and 2015

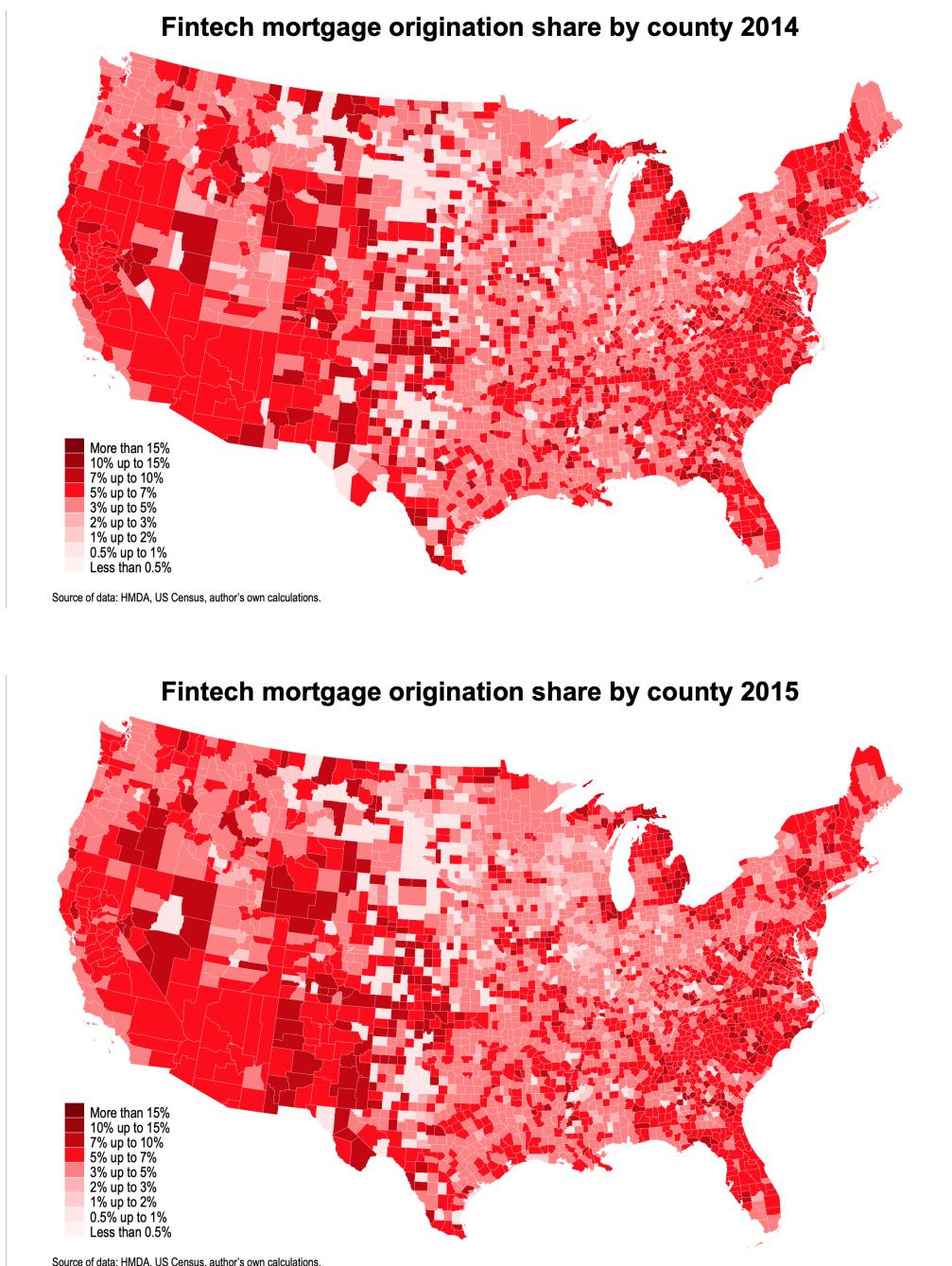
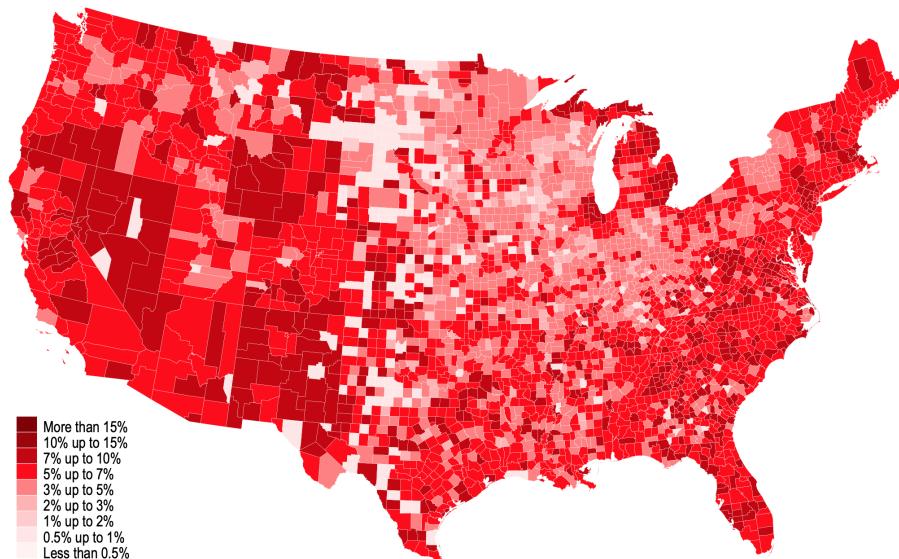


Figure A5: Spatial variation in fintech mortgage originations market share

2016

**Fintech mortgage origination share by county 2016**



Source of data: HMDA, US Census, author's own calculations.

Figure A6: Geographic distribution of sample states

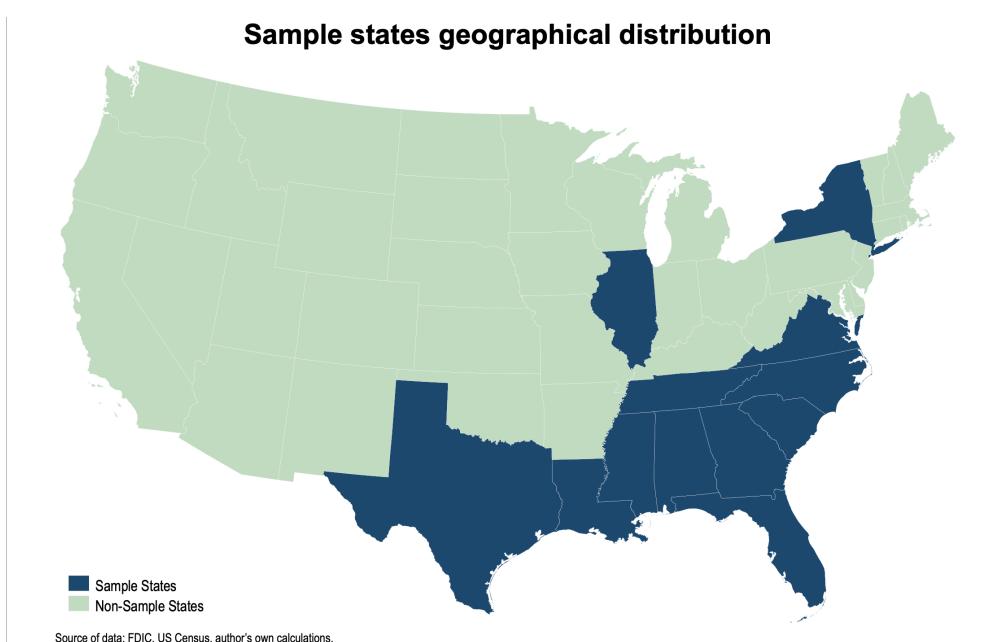


Figure A7: Geographic distribution of bank branches in 2009

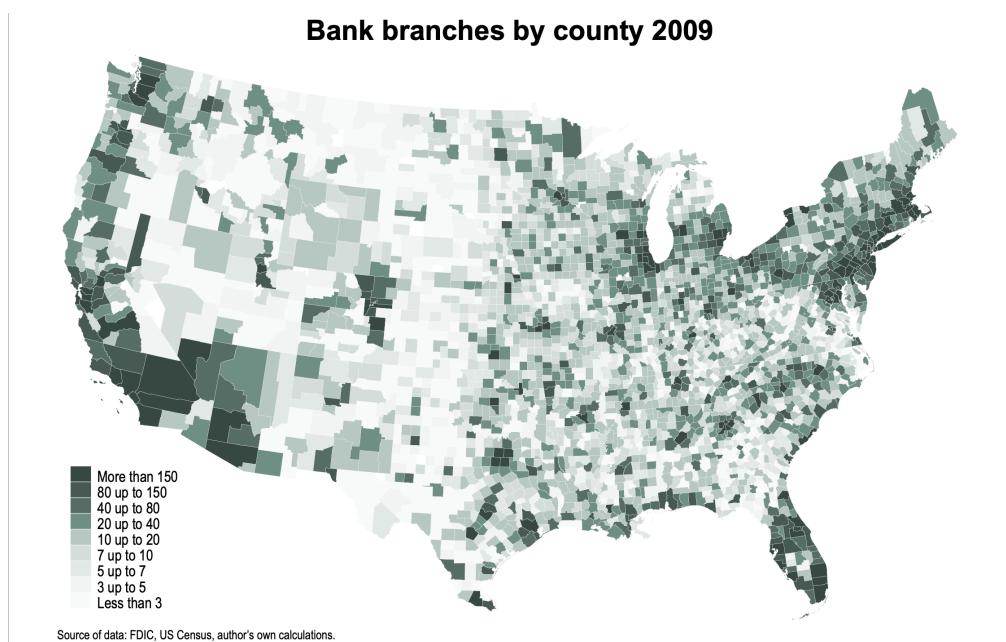


Figure A8: Geographic distribution of bank branches per 100,000 people in 2009

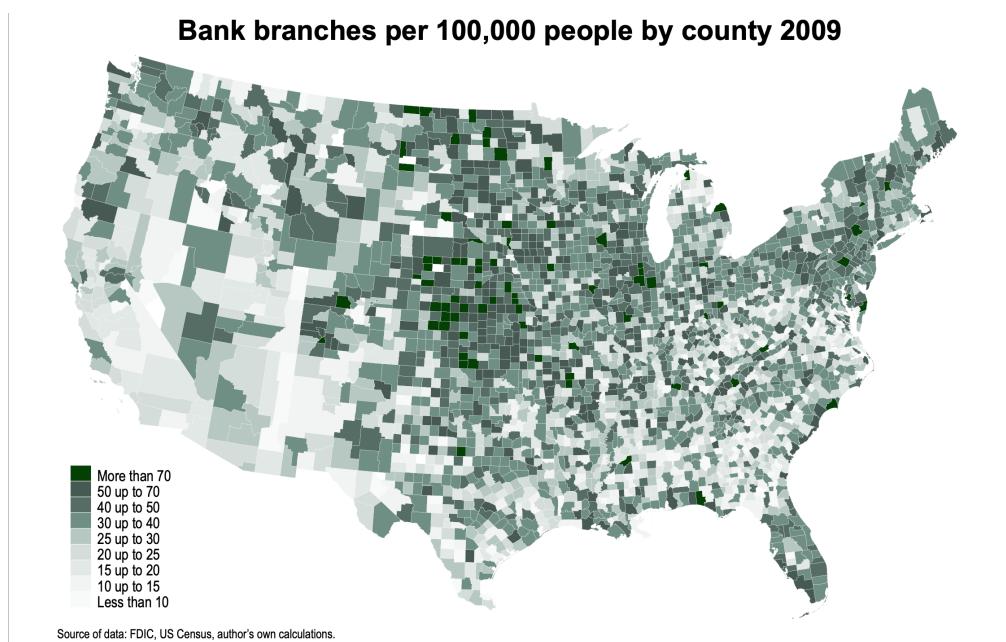


Figure A9: Geographic distribution of US population 2000 US Census

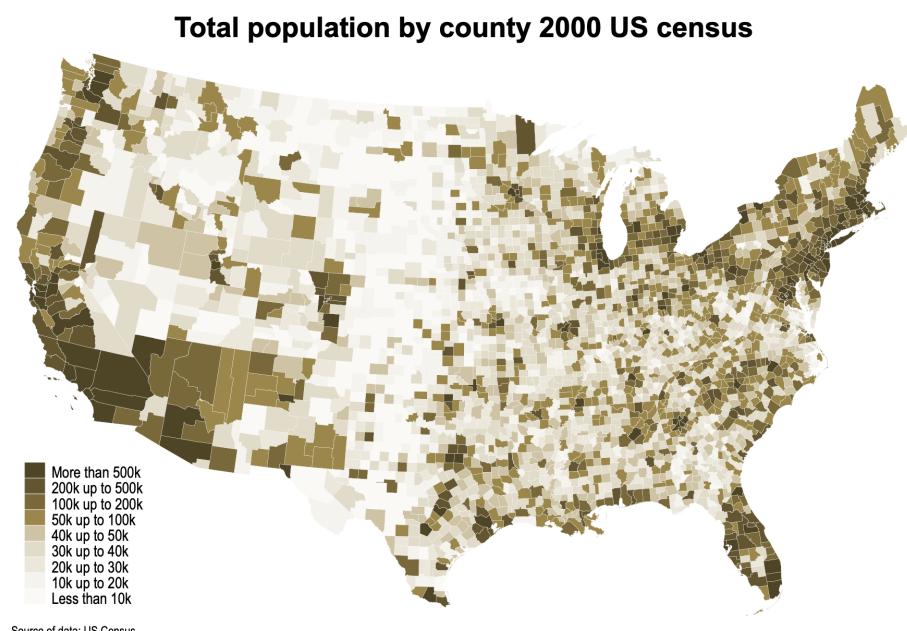


Figure A10: Geographic distribution of branch closings since 2009 up until 2016

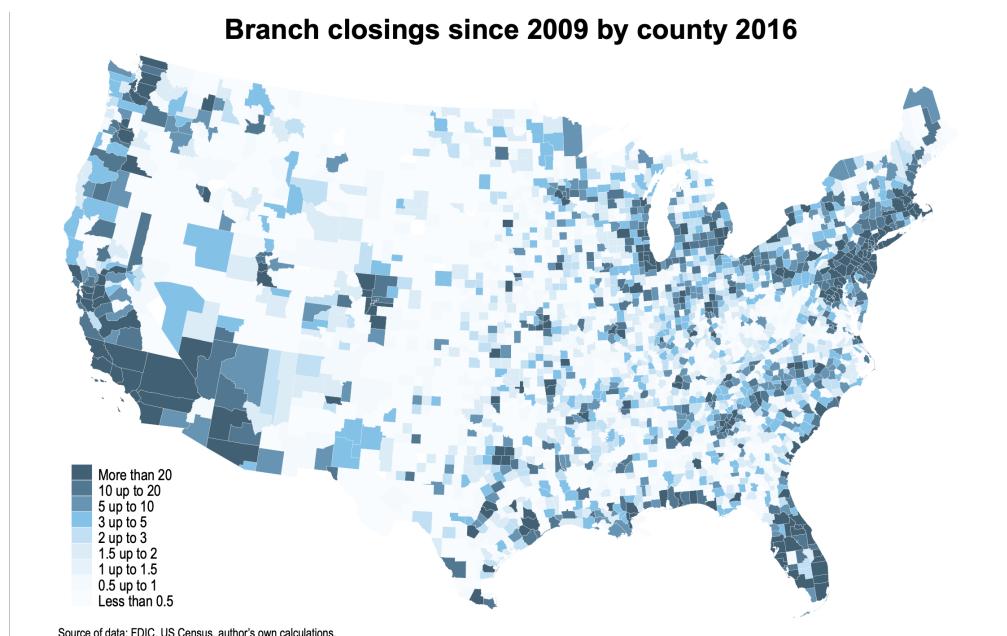


Figure A11: Geographic distribution of branch closings per 100,000 people since 2009 up until 2016

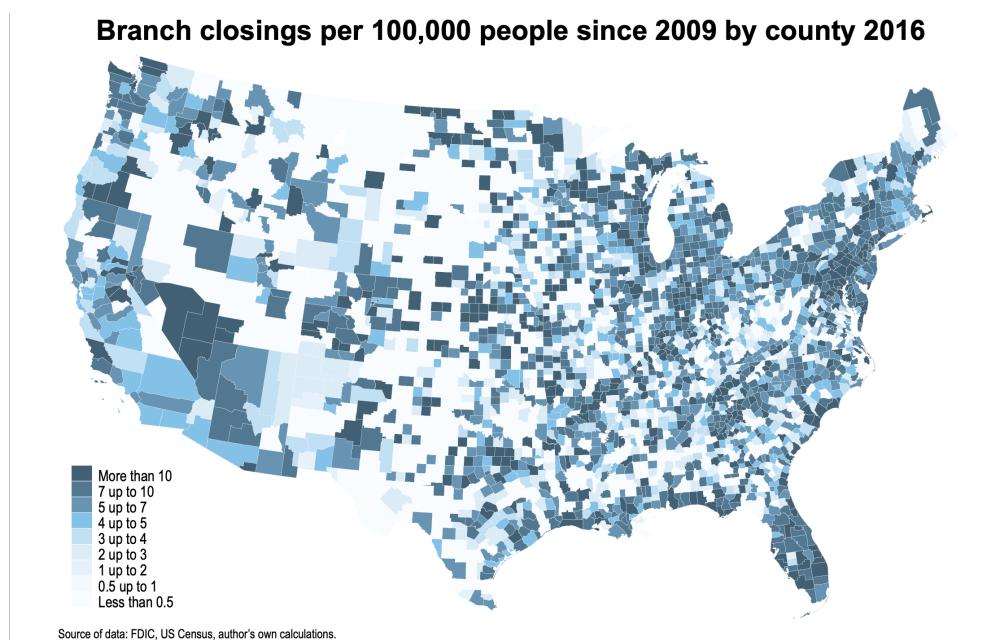
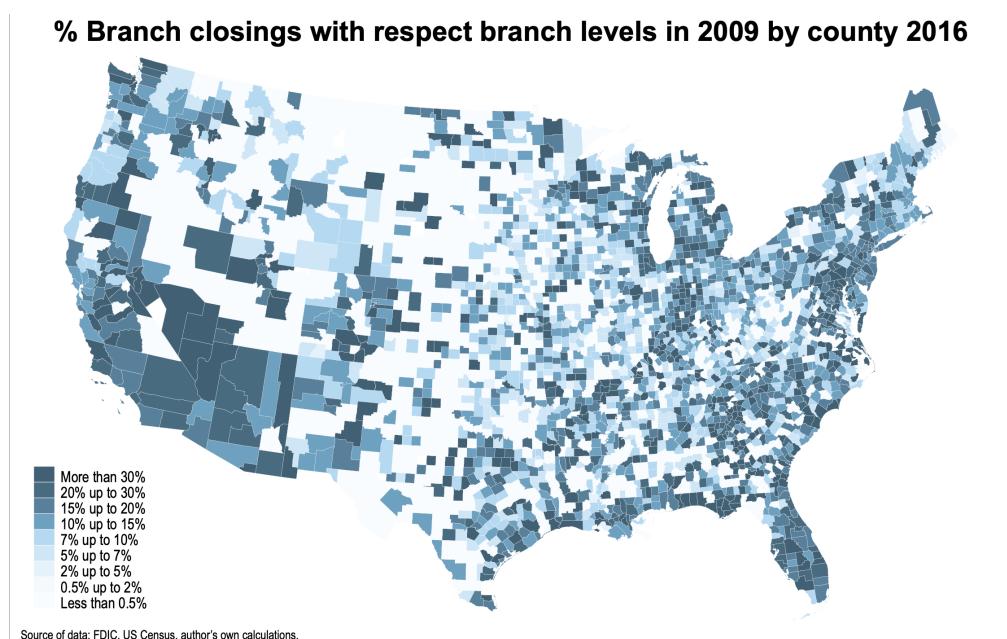


Figure A12: Geographic distribution of the share of branch closings with respect to 2009 bank branch levels in 2016



## B Summary statistics

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

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