Do Minority Banks Matter? Evidence from the Community Reinvestment Act*

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Abstract

This paper estimates the elasticity of minority credit supply to deposit shares of federally designated minority banks. I use within-county tract-level variation in exposure to the Community Reinvestment Act and document that if a census tract loses MDI presence following an MDI-community bank merger, its mortgage minority credit declines by 37% and for up to six years. 1% increase in county market shares of such tracts leads to a 3% decrease in county-level minority homeownership. Tracts that physically lose an MDI -branch experience higher decline suggesting that disruption of minority banking relationships contributes significantly to the observed credit decline.

JEL Classifications: G21, I38

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1 Introduction

In consumer credit markets, ensuring equal and fair access to credit for minorities has been a long-recognized policy goal. Yet, recent academic research shows that minorities continue to experience price discrimination (Bartlett et al. (2021)), inferior quality of banking service (Begley and Purnanandam (2021)), and difficulty in raising external capital (Fairlie et al. (2020)). At the same time there is evidence that social proximity (Fisman et al. (2017)), geographical proximity (Nguyen (2019), Degryse et al. (2011)), personal lending relationships (Drexler and Schoar (2014), Karolyi (2018)), and targeted branching (Allen et al. (2021)) reduce information asymmetries and improve credit outcomes. While the role of traditional banks vis-à-vis credit access for minorities has received much research focus, that of federally designated and mission-driven minority banks, which encapsulate benefits of social, cultural, and geographic proximity, has received less attention. This paper fills this gap.

Officially defined in the Section 308 of the Financial Institutions Reform, Recovery and Enforcement Act of 1989 ("FIRREA"), Minority Depository Institutions (MDIs - Figure 1) are small community banks that are minority-owned or governed and are mandated to serve the local communities they represent[1]. Though MDIs have existed since the American Civil War, they represent only 1.5% of the banking universe in terms of size. Despite their small presence, MDIs are unique as they serve hyper-local minority neighborhoods traditionally underserved by other banks (Toussaint-Comeau and Newberger (2017), Barth et al. (2018)). Accordingly, policymakers have formulated policies that aim to preserve the MDI status in the face of industry consolidation[2]. Using a unique natural laboratory offered by an interac-tion between a long-running federal regulation, the Community Reinvestment Act (CRA), and detailed tract level data on MDIs, I specifically study how mission-driven minority banks impact the minority mortgage credit access and minority homeownership.

This paper makes three contributions. First, I estimate that mortgage credit supply to minorities declines by up to 37 % and for up to six years (Figure 2) in census tracts that lose local MDI presence through a merger with a non-MDI community bank (treatment) relative

[1] Per FIRREA Section 308 -"Minority" means any "Black American, Asian American, Hispanic American, or Native American" - See Appendix- A for more details

[2] https://www.fdic.gov/regulations/resources/minority/sop5-only.pdf

to *within county* tracts that experience an MDI-MDI merger (control). Second, I find that the decline in minority lending is more substantial in geographies that see physical closures of MDI branches post-merger than in geographies where branch ownership merely changes hands. Third, I find that the loss of minority-owned banks at a census-tract level translates to an overall decline of about 3% in minority homeownership at the *aggregate* county level.

An important concern in interpreting these results as causal benefits of MDIs is that mergers and acquisitions reflect endogenous choices of firms in response to local economic conditions; thus, a reversely causal relationship cannot be ruled out. For example, local economic conditions can reduce the credit demanded by MDI customers, leading to MDI-community bank mergers due to declining MDI profitability. Indeed, the aggregate numbers for MDIs have ebbed and flowed with the business cycle (Figure 3).

To overcome this endogeneity concern, I use an instrument based on *a priori* exposure of a census tract to the Community Reinvestment Act (CRA) performance evaluations as a source of exogenous variation in the incidence of MDI-community bank mergers. CRA, a Civil Rights-era law, is unique in that it periodically evaluates banks predicated on their performance in meeting their customers' credit and banking needs in low-medium income census tracts. A healthy CRA appraisal is crucial in obtaining future regulatory approvals for *de novo* branch openings or inorganic expansion through mergers.

The identifying assumptions of this instrumental variables empirical framework are twofold. First, the inclusion restriction requires that CRA evaluation intensity in a census tract predict the incidence of the MDI-community bank mergers in that tract. Second, a tract's CRA evaluation intensity should impact the minority credit supplied *only* through its impact on MDI-community bank mergers, and not directly, the exclusion restriction. A related concern could also be that the CRA examination intensity is not random and instead ebbs and flows with local economic conditions, rendering the instrument equally endogenous as the problematic co-variate.

The intuition behind inclusion restriction being satisfied is as follows: If the supply of CRA eligible credits per evaluated geography is limited, and the CRA examination intensity is highly elevated, multiple banks compete for the same geographic pool of CRA eligible investments. Therefore, at least some MDI-community bank mergers will be motivated for reasons attributed to obtaining regulatory relief vis-a-vis the CRA. Such mergers shall be exacerbated when the community bank acquirers of MDIs are in an expansionary mode or the industry, in general, is in a consolidation phase as favorable CRA evaluations are critical for successfully implementing banks' expansion plans[3]. In the empirical section of this paper, I provide additional evidence corroborating this intuition, as the inclusion restriction is ultimately, testable.

Regarding the satisfaction of the exclusion condition, if high CRA intensity in a tract were to impact minority supply directly, one would expect the minority credit supply to *increase* and not *decrease* on account of higher regulatory oversight (Agarwal et al. (2012), Saadi (2020), Bhutta (2011), Zinman (2002)). What I instead find is that the minority credit *decreases* if estimated in a reduced form or a 2SLS setting, suggesting that the results flow through CRA's effects on reducing local MDI presence. Moreover, as different regulators determine the CRA schedule well in advance and not based on the state of the economy and that CRA intensity may also change due to exogenous updates of tract income levels (Chakraborty, Chhaochharia, Hai, and Vatsa (2020)), the CRA examination intensity is likely independent of local economic conditions.

The loss of local MDI presence resulting from an MDI-community-bank merger can manifest in two forms at a local branch level. Either the erstwhile MDI branch continues to operate as the branch of the consolidated bank or shuts down due to retrenchment. In the case of physical branch closures, all elements, i.e., geographic proximity, cultural proximity, and personal relationships, disrupt abruptly. If branch ownership changes hands, some personnel may be retained, and geographical proximity is not disrupted. If the observed decline is due to the loss of local minority presence, one can expect the results to be more significant for those tracts that saw physical closures of MDI branches, as these cases represent a more complete disruption of minority banking relationships.

[3]There is anecdotal evidence - https://www.bizjournals.com/philadelphia/news/2017/03/23/fulton-financial-united-bancshares-reinvestment.html - of community banks MDI mergers to improve their CRA standing

To test the disruption of relationships channel, I construct a national panel of physical branch address-bank pairs[4] and track it over the last two decades. This procedure allows me to separate instances of branch closures from ownership changes following mergers. I indeed find that the credit decline is more pronounced in the sub-sample of tract observations that see branch closures and as expected, attenuates by about 50% when branches change owners. In further tests, I also confirm that the mortgage denials are not substantially high in tracts that see branch ownership changes. These results lend credence to the dominance of the relationship channel.

Using two different national surveys, I document that losing MDI presence adversely affects minority homeownership at an aggregated county level. First, using the 1% sample of the American Community Survey (ACS), I directly test for homeownership rates by minorities in a country-year as my dependent variable. Second, using the matched survey participants across the March supplement of the Current Population Surveys (CPS), I estimate the probability of a minority household transitioning from owning a home to buying a home. In both cases, I find that a percentage increase in county deposit share of tracts that lose MDI presence following an MDI-community bank merger leads to about 3% decrease in minority homeownership. A decrease of about 40% at a branch level translating to a not unsubstantial 3% impact on racial homeownership gap at an aggregate level provides one estimate of how much MDIs matter in terms of impact on real aggregate variables.

These results have implications from a banking regulatory perspective. Extant regulation, specifically Section 308 of The Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA), works on a "best-effort-basis"[5] to preserve the minority character of MDIs in a merger transaction. Nevertheless, over the last two decades, in non-assisted mergers, MDIs have merged with other MDIs and with non-MDIs with an equal propensity (see Figure 8). To the extent that non-MDI acquisitions of MDIs are partially motivated to gain future regulatory relief, the resultant decline of local minority credit supply and its impact on minority homeownership represents an unintended negative externality of the present regulatory framework supporting MDI supervision. Given that the minority home purchase

[4] By connecting physical branch addresses with US postal address geo-database

[5] https://www.federalreserve.gov/publications/2016-preserving-minority-depository-institutions-section-308-firrea.htm

market has a size of about \$250 billion in 2017, an upper limit back of envelope estimate of this negative externality is about \$ 92 billion (37% decrease of the total).

My paper is related to a few different strands of literature. First, it is related to the vast literature on the role of banks in overcoming capital market frictions. Petersen and Rajan (1994) provides evidence of relationship lending working through its impact on quantities rather than prices. Diamond (1991) suggests that the duration of monitored banking relationships helps overcome future costs related to borrower moral hazard. Regarding the impact of the competition itself, Boot and Thakor (2000) finds that inter-bank competition tends to increase relationship lending but at a lower marginal benefit to the borrower. Fisman, Paravisini, and Vig (2017) estimates the impact of shared cultural background on credit access. In this paper, I find that the loss of an in-group bank has a significant negative impact on access to credit for the represented community.

Second, my paper contributes to the literature that evaluates financial inclusion mechanisms. Burgess and Pande (2005) finds that rural banks matter for poverty alleviation. Banerjee, Duflo, Glennerster, and Kinnan (2015) re-examines the role of microcredit in fostering local development and finds mixed evidence. Gilje, Loutskina, and Strahan (2016) points to the continued importance of branch networks in financial integration, Nguyen (2019) confirms this using large bank mergers induced branch closures. This paper contributes to this literature by quantifying the impact of MDI presence for a small geography's minority homeownership.

Third, my paper is related to the extensive literature on banking regulation's intended or unintended consequences. Specifically, regarding the CRA, Chakraborty, Chhaochharia, Hai, and Vatsa (2020) estimates the costs and benefits of CRA on societal welfare, Agarwal, Benmelech, Bergman, and Seru (2012) shows the evidence of riskier mortgage lending by banks around CRA examinations, Saadi (2020) studies the role of CRA on mortgage lending during the housing boom. Bostic and Lee (2017) studies the impact of CRA on small business lending in census tracts. Through this paper, I document a scope for improvement in the CRA by estimating the size of one of its unintended consequences on minority-owned banks.

This paper also suggests a role for more stringent control over MDI supervision by providing greater authority to bank regulators over non-assisted MDI mergers.

2 Data

For my empirical analysis, I use data from multiple sources. In this section, I provide a brief overview of various data sources. Institutional background of MDIs is available in Appendix A. A detailed list of all the main variables used along with their definitions and respective sources is available in Appendix B

Following extant banking literature, I obtain bank-level balance sheets, income statements, and other structural variables from Reports of Condition and Income (Call Reports) and Uniform Bank Performance Reports (UBPRs) also provided by the FFIEC.

Data on all active and newly charted MDIs is available through FDIC. FDIC maintains a list[6] and tracks the insured MDIs it supervises, i.e., state-chartered institutions that are not members of the Federal Reserve System (Federal Reserve), as well as MDIs supervised by the Office of the Comptroller of the Currency (OCC) and the Federal Reserve. A detailed institutional background of MDIs is available in Appendix A.

I use the Business Combinations report available through FDIC's Reports of Changes to Financial Institutions & Office Structure database[7] to tabulate the bank M&A data. Business Combinations include both FDIC-assisted merges, i.e., absorptions in case of bank failures, and voluntary combinations involving non-assisted consolidations, absorptions, and mergers. I also augment the Business Combinations database with data on failed banks[8] as well as the data on community banks[9], available via FDIC's community banking initiative. Using these databases, I can identify MDI mergers, MDI failures, the type of acquiring bank (MDI Vs. Community Banks), and construct an event timeline pre and post the MDI mergers.

[6] https://www.fdic.gov/regulations/resources/minority/mdi.html
[7] https://www5.fdic.gov/roc/Default.aspx
[8] https://www.fdic.gov/Bank/individual/failed/banklist.html
[9] https://www.fdic.gov/regulations/resources/cbi/data.html

The minutest geographical level at which credit data are available, along with the race, geography, and time dimensions (HMDA database), is the census tract. Census tracts are homogeneous geographical areas demarcated for Census purposes to define neighborhoods having 4,000 to 8,000 residents. Area-wise, their sizes are adjusted for population density (Figure 1), with the average area being 1.5 square miles. The American community surveys and decennial census provide rich demographic data at a tract-year level. However, data on banking presence is not directly available at this level. The data on bank deposits are disaggregated at most up to the zip-code level, and noisily so. Zip-codes (about 43,000 in the US) provide lesser granularity than census tracts (about 73,000 in the US).

To construct my data panels at the bank-tract-year level, I carry out a geocoding exercise using branch addresses and latitude-longitude information from the The Summary of Deposits[10], (SOD), using ArcGIS software to map the banking data to the tract level. SOD is an annual survey of branch level deposits as of June 30th of all FDIC-insured institutions. It provides branch-level deposits, branch addresses including ZIP codes, and from 2008 onward, also the latitude and longitude of the bank branches. Using the ArcGIS software, I carry out a detailed geocoding exercise and map the available geographic information, i.e., geographic coordinates and zip-codes(in case of missing coordinates) of bank branches to their home census tracts. As a result, I can determine the geographical footprint: i.e., the number of branches, bank head offices, and market shares of a bank at a very minute geographical (bank-tract-year) level. Appendix D.1 presents the details and summary statistics of the geocoding procedure.

I integrate the banking data - which include FDIC provided credit, deposit, MDIs, Community bank, SOD, mergers, reports of changes, and business combinations - and the Census data using geographic identifiers that are matched across three different census vintages (1990, 2000 and 2010), this process achieves a better *nominal* join with the banking and census databases. Using the combined database, I conduct empirical analysis at a census tract-year and aggregate the findings to the county-year and the household-county-year levels.

[10]https://www.fdic.gov/regulations/resources/call/sod.html

To conduct household analysis, I use the March supplement of the Current Population Survey (CPS), which records the survey participants' annual social and economic characteristics. Further, using the longitudinal design of the CPS, I match participants across survey years to derive homeownership transition probabilities. Additionally, I also use data from the American Community Survey(ACS) to conduct analysis on county homeownership.

3 Summary statistics

3.1 MDI Summary Statistics

The sample period for this analysis runs from 2001 through 2018, which is the entire range of time series data available through FDIC. Table 1, Panel A-I presents comprehensive summary statistics including balance sheet, concentrations of credit, and financial performance variables for the MDIs. For comparison, the next panel provides similar statistics for non-MDI community banks.

In terms of the balance sheet, a median MDI is about $173 million in size, and core deposits fund about two-thirds of its assets. Core deposits represent stable deposits by bank customers and include, among other items: checking accounts and small-denomination timed deposits. A median community bank is similar in size ($138 million), but it is more dependent on core deposits for funding (75%). That non-core deposits form a non-trivial part of MDI funding (4% Vs. 2% on average) is not surprising given the historical and continued presence of government-encouraged deposit programs. For both MDIs and community banks, net loans and leases comprise about two-thirds of the balance sheet. Dependence on short-term funding, such as repurchase agreements and federal funds, is more (19%) for MDIs than community banks (11%). Pre-recession, both the bank categories had similar dependence on short term non-core funding, about 22%, post-recession the community banks have drastically reduced their dependence on short term non-core funding (to about 5%). For MDIs, post-recession short-term funding dependence is still around 11%.

Along the dimension of the credit concentration, residential mortgage lending for single-family homes is comparable between MDIs and community banks. However, there are perceptible differences in lending for multifamily housing. Unlike community bank service areas, the primary service areas of MDIs are high minority and poor neighborhoods, places where low-income multifamily housing is standard. MDIs also lend much more in percentage terms to businesses backed by commercial (non-farm non-residential) real estate than community banks do. Lending for commercial and construction purposes is similar for both bank categories.

Financial performance-wise, MDIs are less profitable and less efficient than their community banking counterparts. On average, MDIs have negative NOPAT margins, attributable to both loan losses and operational inefficiencies. The inefficiency ratio (overhead expenses to income ratio) is much higher, on average, for MDIs (about 90%) than it is for community banks (74%). MDIs also have higher loan loss provisions and charge-offs than community banks, but both have the same net interest margins.

These data suggest that MDIs are similar to non-MDI community banks regarding their balance sheet size and amount of lending activity. However, some differences remain between these two bank types, in that MDIs have a relatively more volatile funding base and higher operational inefficiencies. MDIs tend to operate in relatively poor and traditionally credit-rationed communities, leading to inferior financial performance.

Table 1, Panel B-I presents summary statistics on mortgages originated for owner-occupied home purchases by different types of MDIs. For each MDI type, about 60-80% of mortgages originated are given to the minority that the bank represents. Table 1, Panel B-II presents summary statistics for community banks. Compared to MDI, the fraction of mortgage lending to minority applicants stands at a modest 20%.

Table 1, Panel C-I and Table 1, Panel C-II present summary statistics for both MDIs and community banks by type of mortgages originated for purposes of owner-occupied home purchase. It can be inferred from the two panels that the distribution of mortgages issued by both MDIs and community banks is quite similar across all different loan types. On expected lines, the largest type of mortgages are conventional mortgages for 1-4 family homes, with both bank types responding equally to riskier but government-insured FHA and VA mortgages.

At a firm-year level, MDIs and Community banks are quite comparable in terms of the accounting and credit parameters, although MDIs are operationally more inefficient. In terms of asset base, MDIs represent less than two percent of the banking universe. About 90% of MDIs have assets less than $1 billion and, at the 50th percentile, have only about 30 operating branches in a large metro. For comparison, similar-sized non-MDI community banks have 120 branches in a major metro. Previous research (Toussaint-Comeau and Newberger (2017) and Breitenstein et al. (2014)) using descriptive statistics has reached a general conclusion that MDIs do play a unique role but are primarily hyper-local in impact and serve markets that the larger banks traditionally underserve.

3.2 Merger Sample

Table 1, Panel C-III shows that control and treated tracts in my sample are similar along banking networks and demographics. Both the treated and the control tracts have the same number of branches of traditional banks and MDIs, similar numbers of households and income levels. Both the treated and control tracts are at 92-93% of the MSA income level, have 3 total branches, and 1 MDI branch. However, some significant differences remain in that, control tracts on an average have higher minority population percentage but lower average minority credit supplied. Moreover, distribution of minority mortgage credit exhibits a fatter right tail for treated tracts.

To address this, I use log scale for my dependent variables in the empirical analysis and conduct a difference and in difference analysis augmented by an instrument variable approach. This allows me to control for time varying covariates and also also establish the pre and post trends in mortgage origination that I report graphically. The next section details the main result and empirical approach.

4 Identification and empirical framework

4.1 Does MDI presence lead to higher minority lending?

I begin my empirical analysis in equation *1* by testing to nullify the hypothesis that the observed spatio-temporal differences in minority credit supply are independent of MDI presence in local banking markets. Critical determinants of the variation in geographical homeownership rates are the economic standing and the racial composition of the geography (Haurin et al. (2007)). These factors influence the racial homeownership gap, and therefore the local minority mortgage credit supply, by simultaneously affecting many household primitives such as marital status, years married, duration of the rental spell, and family size, income, and wealth. The following model tests for the incremental effect of local MDI deposit share in a tract on minority credit supply using a three-way interaction between MDI presence, racial composition, and relative financial standing of the geography.

(1)

$$\begin{aligned} log(y_{i,t}^{minority}) = \alpha + \beta_1 z\mathcal{S}_{i,t} + \beta_2 z\mathcal{R}_{i,t} + \beta_3 z\mathcal{M}_{i,t} + \beta_4(z\mathcal{S}_{i,t} \times z\mathcal{R}_{i,t}) + \\ \beta_5(z\mathcal{R}_{i,t} \times z\mathcal{M}_{i,t}) + \beta_6(z\mathcal{M}_{i,t} \times z\mathcal{S}_{i,t}) + \\ \beta_7(z\mathcal{S}_{i,t} \times z\mathcal{R}_{i,t} \times z\mathcal{M}_{i,t}) + \beta_8 X_{i,t-1} + \beta_{i,t}(i \cdot t) + \gamma_i + \theta_{c,t} + \varepsilon_{i,t}, \end{aligned}$$

Where:

For a census tract i in year t,

$z\mathcal{S}_{i,t}$ = MDI tract deposit share,

$z\mathcal{R}_{i,t}$ = Tract to MSA family income ratio,

$z\mathcal{M}_{i,t}$ = Minority percentage in a tract,

γ_i and $\theta_{c,t}$ are tract and county-year fixed effects respectively,

$(i \cdot t)$ controls for linear time trends

The dependent variable $log(y_{i,t}^{minority})$ is the natural logarithm of the amount of mortgages extended to minorities in a for owner-occupied home purchases. The main explanatory variable is the three-way interaction of the variables $z\mathcal{S}_{i,t}$, $z\mathcal{R}_{i,t}$, and $z\mathcal{M}_{i,t}$. $z\mathcal{R}_{i,t}$ is a commonly used regulatory ratio that determines a tract's LMI standing under both the CRA and HMDA regulations. It is the ratio of a tract's median family income to the metropolitan area's median family income. Since I use standardized negative values, increasing values of $z\mathcal{R}_{i,t}$ imply that the tract is relatively impoverished. $z\mathcal{M}_{i,t}$ is the percentage of the minority population in a tract in a given year. $z\mathcal{S}_{i,t}$ is the deposit market share of MDIs in a tract-year. β_7, the coefficient of interest, captures the simultaneous effect of MDI presence and tract's economic and racial composition on minority credit supply.

The coefficients in equation *1* are obtained in the presence of *county-year* fixed effects implying that the identification is based on a comparison between two tracts *within* the same county in a given year. Comparing two tracts across the US will result in a naive comparison as different regions have different demographic compositions. Conservatively, the model also controls for any time-invariant tract characteristics by including tract fixed effects *and* additionally includes tract-level linear time trends. Presence of these fixed effects simultaneously subsume tract-year level mortgage credit demand and local business cycles. Finally, the model also controls for a vector of *lagged* tract-level controls, $X_{i,t-1}$, including the number of households, log of tract deposits, tract-MSA family income ratio, minority percentage, Herfindahl Index of bank deposit shares, and the number of physical branches in the tract.

Column (4) in Table 2 presents the results of the fully saturated model involving the three-way interaction term. The slope coefficient loads positively and is statistically significant, I therefore, reject the null hypothesis that MDI banks do not matter for a tracts credit minority credit supply. For straightforward interpretation, I graphically plot four different scenarios related to tract income levels and minority percentage interacted with MDI presence in Figure 4.

The figure presents the change in the dependent variable (natural log of minority mortgage lending) for a 0-100% change in MDI presence in a tract for $\pm 1\sigma$ (standard deviation) change in both the tract minority percentage and the MFI ratio. All other control variables are at the sample means. It is apparent from Figure 4 that in all scenarios but one, an increase in MDI presence increases the amount of minority lending. The one scenario where MDI presence does not strengthen the relationship pertains to very rich and very minority heavy tracts. Such tracts represent a mere 0.5% of the sample observations. From the figure, it also can be inferred that having no MDI to only MDI in a tract can lead to anywhere between a 5% to a 40% increase in tract-level minority credit.

Results in this section only help corroborate a significant correlation between the presence of an MDI and the minority credit supply in a given locality. These results do not imply causation. One concern is that despite controlling for fixed effects and time trends, the market share of MDIs likely represents an endogenous decision of banks to increase or decrease their market presence purely as a response to local economic conditions and competition[11]. In the following sections, I address this concern using a qausi-random natural experiment design to generate plausibly exogenous variation in MDI market share.

4.2 Main Results

4.2.1 Difference in differences estimation

I use MDI merger-event as a source of exogenous change in MDI market share in a locality, the endogenous co-variate in Equation *1*. Prior literature has extensively used merger induced changes in market concentration to study various real effects such as crime (Garmaise and Moskowitz (2006)), branch closures induced credit supply decline (Nguyen (2019)), and the direct impact of mergers on small businesses (Degryse et al. (2011)). I use the merger event to estimate the impact of the loss of a dedicated minority bank on a neighborhood's minority credit supply, first, in a generalized difference in differences framework as follows:

$$log(y_{i,t}^{minority}) = \alpha_i + \gamma_{c,t} + \beta_1 \mathbf{Treat}_i \cdot \mathbf{Post}_t + \beta_2 X_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

[11] $z\mathcal{S}_{i,t}$, is therefore, not orthogonal to $\varepsilon_{i,t}$ in violation of strict exogeneity

Here, a tract i is assigned *treatment* if the only serving MDI bank in the tract gets acquired by a non-MDI community bank (MDI-CB merger), resulting in a tract losing presence of special banks that had MDI status. Control tracts are those tracts *within* the same county that experience a merger between two MDIs. $X_{i,t-1}$ is a set of lagged tract-level controls. $\mathbf{Post}_t$ is an indicator that takes on a value of 1 if the year is a post-merger year. To ensure that credit supply is not affected by the size of the acquiring financial institution, I require that all the banks in the merger sample, whether target or acquirer, MDI or non-MDI, be community banks[12]. Provided that the identifying parallel trends assumption is satisfied and the treatment is randomly assigned, the coefficient of interest, β_1, is unbiased and estimates the impact of the loss of MDI status on a geography's minority credit supply.

I report the results of Equation 7 in columns (1) and (2) of Table 3. Specification in column (1) compares census tracts nationally, while in column (2), county-year fixed effects ensure that the comparison is *within* a county. I also plot the coefficients of a more general model as given below in Figure 2 to test the parallel trends assumption.

$$log(y_{i,t}^{minority}) = \alpha_i + \gamma_{c,t} + \beta_t \cdot \sum_{\tau} \mathbf{Treat}_i \cdot \mathbf{I}_{t=\tau} + \beta_2 X_{i,t-1} + \varepsilon_{i,t}, \tag{3}$$

Plotting the year dummy interactions with the treatment indicator provides a visual test of the parallel trends assumption. Figure 2 confirms the presence of parallel trends as pre-merger coefficients are statistically indifferent from zero. It can also be inferred from the figure that minority lending in a tract remains depressed up to 6 years post the MDI acquisition. Coefficient of interaction in Table 3 column (2), confirms that on an average, a treated tract experiences a decline of about 32.9% in minority mortgage lending relative to a *within* county control tract following the merger event. Nationally (Column 1), these differences are somewhat attenuated but remain negative.

A remaining concern is that the presence of parallel trends alone does not ensure strict exogeneity. Internal validity of a generalized difference in differences design still requires

[12]Using the official FDIC definition of community banks, see Figure C.3

that the treatment assignment be random. For example, a counter rationale can be that local economic conditions render the primary customers of MDIs economically worse-off. As a result, MDIs become less profitable and get acquired by other community banks making the relationship reversely causal. To establish this, I supplement the difference in differences framework using an instrumental variables approach whereby the *a priori* exposure of a tract to the regulatory performance evaluations acts as a source of plausibly exogenous variation in the probability of treatment.

4.2.2 Instrumental variable estimation

The instrumental variable that I use is micro-founded from the incidence of regulatory performance evaluations faced by banks on account of the Community Reinvestment Act (CRA) of 1977. In the following sub-sections, I discuss the CRA context, construction of the instrument, key IV assumptions of inclusion and exclusion restrictions, and the statistical results using the IV estimation. Previous literature (Agarwal et al. (2012)) has used the *timing* of CRA examinations as a source of exogeneity to assess the level and quality of mortgage lending done by banks around the exams. The instrument that I use is the examination intensity at *census tract-year* level.

4.2.3 Background: CRA context and instrument variable construction

To understand the intuition behind the instrumental variable, I begin by briefly establishing the contextual relevance of the Community Reinvestment Act (CRA), a civil rights era regulation. CRA is a long-running program (active since 1977 till the present) that encourages US commercial banks to meet the credit needs of low and moderate-income neighborhoods in areas where banks have a market presence. The rationale behind enacting the CRA was to encourage commercial banks to eliminate the discriminatory banking practice of *redlining* or the systematic denial of banking services to the demarcated poor, especially in minority neighborhoods.

Under the CRA, banks are subject to periodic and comprehensive onsite regulatory examinations that last several months. Non-compliance or even below-par performance in the CRA evaluation entails high economic and reputational costs for the bank. For instance, any future expansion: be it organic such as through opening of *de novo* branches or inorganic via future acquisitions, is unlikely to get regulatory approval if the CRA performance of a bank is unsatisfactory.

The most important criterion of the CRA performance evaluation is how correlated a *bank's* distribution of home mortgages (and C&I loans) is with the *aggregate* distribution of mortgages (and C&I loans) across median family income levels in a bank's primary assessment areas. From a CRA lending test perspective[13], a bank must not lag behind the aggregate in the left tail of the income distribution, i.e., when serving the credit needs of low-to-moderate income (LMI) and minority customers[14].

The fact that multiple banks compete for the same CRA eligible credits in a given tract and that the evaluation is on a relative basis are important aspects in the context of micro-founding my instrumental variable. I use the mean CRA intensity $\overline{\mathcal{C}}_{i,t}$ of a tract i in years t and $t+1$ as an instrument to predict MDI-non-MDI mergers where the annual CRA intensity $\mathcal{C}_{i,t}$ of a tract i in year t is calculated as below:.

$$\mathcal{C}_{i,t} = \sum_{b} \mathcal{S}_{b,i,t} \times \frac{\mathbf{Exam}_{b,t}}{\mathcal{R}_{i,t}} \tag{4}$$

Where: For a bank b, census tract i in year t,

$\mathcal{S}_{b,i,t}$ = Share of tract deposits held by the bank b in year t in tract i,

$\mathbf{Exam}_{b,t}$ = Takes on a value of 1 if a bank b undergoes a CRA performance evaluation in the year t

$\mathcal{R}_{i,t}$ = tract MFI ratio.

[13]the lending test has the highest weights in overall CRA examination

[14]If a tract has median family income less than 80% of the larger metropolitan area's median family income

Intuitively, $\mathcal{C}_{i,t}$ is the fraction of tract deposits that are undergoing CRA evaluation in a given year scaled by tract income (richer tracts will decrease the CRA intensity), and it follows that $\overline{\mathcal{C}}_{i,t}$ provides a sense of immediate (t=0) and impending (t=+1) CRA intensity in a tract. The reason for using the mean CRA intensity over the annual measure is twofold: First, under the reasonable assumption of proactive action on the part of the banks, both *immediate* CRA exam and *impending* CRA evaluations affect the present behavior of the examinee (Reid et al. (2013)). Second, CRA exams typically last several months and may spread across two consecutive calendar years, in which case an annual CRA intensity may only noisily proxy geographic CRA pressure[15]; thus an average measure is preferred. I obtain the data necessary for the construction of the instrument at a census tract level by combining the CRA composite exams database with the geo-enhanced summary of deposits (SOD)[16].

4.2.4 Inclusion restriction

The first identifying assumption of the instrument variables identification is the **inclusion restriction**: that the instrument should predict the assignment of treatment. The rationale behind the CRA intensity instrument satisfying this condition is that increased CRA pressure will affect at least some similar-sized community banks, having the same geographic footprint as MDIs, to consider gaining CRA credits via inorganically acquiring local MDIs. Anecdotally, there have been a few cases of community bank acquisitions or of investments in MDIs to improve future CRA compliance[17].

It is pertinent to note that *enshrined*[18] in the CRA law is the fact that additional CRA benefits for direct investments along with other collaborative partnerships in MDIs is will earn majority-owned banks the much-coveted CRA credits. A highly elevated consolidation activity among smaller community banks in recent years[19] (see also Figure C.4), has further

[15] My IV results do not change in signs if I use the annual measure, they are slightly attenuated in magnitude and mostly statistically significant

[16] This matching process requires non-exact string matching using bigram fuzzy matching technique as identifiers are not consistent across the different regulators

[17] https://www.bizjournals.com/philadelphia/news/2017/03/23/fulton-financial- united-bancshares-reinvestment.html

[18] https://www.fdic.gov/regulations/resources/minority/collaboration/resource-guide.pdf

[19] https://www.fdic.gov/bank/analytical/quarterly/2017-vol11-4/fdic-v11n4-3q2017-article2.pdf

required the acquirering banks be in CRA *good books*. All these factors create an upward CRA compliance pressure on community bank acquirers of leading to MDI-CB mergers.

I do find in the sample that in the years following their MDI acquisition, CB acquirers of MDIs were at least twice as active in M&A activity compared to the MDI acquirers of MDIs. As seen in Figure 5, non-MDI acquirers of MDIs acquired 85 other community banks within five years of their MDI acquisition, with about 80% of those M&As occurring *within* first year following the MDI acquisition. On the other hand, MDI acquirers of MDIs acquired less than 40 other banks or were less than half as active in M&A activity.

Besides a significant correlation, the internal validity of the CRA intensity instrument also requires that the instrument be exogenous to a tract's economic conditions. Moreover, the instrument should not have predictive power over other types of MDI mergers. Regarding the former, variation in tract-level CRA intensity stems from a variety of reasons exogenous to a census tract. At any given time, different banks in a tract are overseen by up to three different federal regulators[20] each having their pre-determined schedules and constraints in conducting the CRA evaluations that are unrelated to a tract's economic conditions. Moreover, events such as the decennial census and metro boundary re-classifications released by the Office of Management and Budget (OMB) exogenously (Chakraborty et al. (2020)) change the relative income of a tract, and finally, simply due to entry, exit, and failures of banks in a tract, the market shares change, at least partially exogenously.

If the merger activity among non-MDI banks is impending, and booming, then the CRA compliance pressure is more binding *ex-ante* on community bank acquirers of MDIs; otherwise, future acquisitions shall be challenging to close for want of CRA compliance. Figure 6 shows this insight visually. The figure plots the change in bank-level CRA intensity faced by the average *acquirer* in different categories of MDI mergers (MDI-community bank(MDI-

[20]the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), and the Board of Governors of the Federal Reserve System

CB) merger, an MDI-MDI merger, and as a reference, CB-CB mergers too) in years leading up to the acquisition. The bank-level CRA intensity is calculated as follows:

$$\mathfrak{B}_{b,t} = \sum_i \overline{\mathcal{C}}_{i,t} \times \mathfrak{i}_{b,i,t} \tag{5}$$

Where:

$\overline{\mathcal{C}}_{i,t}$ = the mean of $\mathcal{C}_{i,t}$ defined as in Equation 4,

$\mathfrak{i}_{b,i,t}$ = fraction of the annual bank deposits represented by tract i in year t

Aggregated in this manner, $\mathfrak{B}_{b,t}$ renders a sense of CRA intensity faced by the acquiring bank in a given year. Strikingly, and as can be visibly inferred, non-MDI acquirers of MDIs experience a steeply increasing CRA pressure in the years leading up to the MDI acquisitions. In the year of the MDI merger, the CRA pressure increase experienced by the non-MDI acquirer of MDI is about two standard deviations higher than that experienced by acquirers in either MDI-MDI acquisitions or CB-CB acquisitions (both of which effectively hover around 0). Intuitively, this implies that non-MDI acquirers of MDIs are operating in geographies where they face intense competition for available CRA credits as many other banks in their local service area are also undergoing (or about to) CRA performance evaluations. Since non-MDI acquirers as a group are going to be ex-ante very active in M&A activity in the years following their MDI acquisition, Figure 5, these may look at MDI acquisitions as a form of pro-active CRA compliance, thereby increasing the probability of an MDI takeover by a non-MDI bank.

4.2.5 Exclusion restriction

The second identifying assumption in IV estimation is that the instrument should affect the levels of minority lending only through its impact on MDI-non-MDI mergers and not directly, the **exclusion restriction**. The case for the exclusion restriction - That CRA intensity affects the level of tract minority lending only through its impact on MDI-CB mergers and not directly - being satisfied is as follows: For, if the CRA intensity (therefore a higher fraction of local area banks undergoing CRA evaluations) were to affect minority lending *directly*, one would expect that a higher CRA examination intensity would tend to an *increase* and not *decrease* in the amount of CRA eligible lending (Agarwal et al. (2012)) to poor minority customers, as these loans would qualify for positive CRA credits.

What I observe and report in the data is the *opposite* effect. The level of minority lending *decreases* with higher CRA intensity, as is clear from reduced form and 2SLS estimates. This implies that the mechanism at play here is that CRA intensity is affecting the level of minority lending *indirectly* through increasing the probability of MDI-CB merger in a tract and causing an important source of minority loan supply (MDIs) to cease to exist in the affected geography which leads to a decrease in the minority credit supply.

4.2.6 IV estimates

I instrument the treatment variable in Equation *3* with the mean CRA intensity to generate plausible exogenous variation in MDI-CB mergers in order to interpret the difference and differences results of the previous section, causally. Following Windmeijer and Santos Silva (1997) and Wooldridge (2010) for IV estimators in case of endogenous binary regressors, I first estimate the following linear probability model.

$$(\text{Treated} = 1 \mid \overline{\mathcal{C}}, Controls) = \alpha + \gamma_{c,t} + \beta 1 \overline{\mathcal{C}}_{i,t} + \beta 2 \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \tag{6}$$

Where, $\overline{\mathcal{C}}_{i,t}$ is the mean CRA intensity as defined above and $\mathbf{X}_{i,t-1}$ is the same vector of lagged tract-level controls that include the number of households(in '000s), minority percentage, tract-MSA family income ratio, Herfindahl Index and the number of branches in a tract.

$\overline{\mathcal{C}}_{i,t}$ loads statistically significantly (P-value < 0.01, $\beta = 21.07$). Next, to avoid the "forbidden" IV regression (whereby the predicted values from the first stage are directly substituted in lieu of the endogenous binary regressor as the second stage), I first transform the data by predicting treatment probabilities and estimate $\widehat{Treat}$. In the second stage, I use the predicted $\widehat{Treat}$ as an *instrument* for the endogenous treatment variable and re-estimate equations 7 and 3 under the 2SLS IV framework.

The IV results are presented in Table 3 in column (4). Comparing the β_1 under the OLS and IV models, I find the usual case of IV estimate ($\beta = -0.3731$) being about 25%-30% larger (Card (2001)) than OLS estimate ($\beta = -0.3292$). The first stage of the IV is significant and the IV ($\widehat{Treat}_i \cdot \mathbf{Post}_t$) predicts the interaction term ($\mathbf{Treat}_i \cdot \mathbf{Post}_t$) with a t-statistic of 8.23 and slope coefficient of 0.902. The Sanderson and Windmeijer test for weak identification yields a F-statistic of 72.26, suggesting a strong first stage and IV identification, while the p-value on the under-identification test is 0, having χ^2 of 85.28.

5 Channels of minority credit supply decline

Following an MDI-community bank merger, a local neighborhood may experience one of the following outcomes: Either the MDI branch physically closes down or continues operations as a non-MDI branch under new ownership. Depending on the outcome, the impact on local minority credit supply will be different. Although, in both the scenarios, the census tract will still see disruptions of the minority lending relationships, in the case of an ownership change, the decline in minority credit supply will not be as severe as geographical proximity is still present. However, when a branch physically closes down, both geographical *and* cultural proximity is lost. Moreover, frictions in forming new lending relationships (Argyle et al. (2020)) and abrupt loss of personal relationships (Drexler and Schoar (2014)) will mean that the decline in minority credit lending will be relatively higher. In this section I test this hypothesis.

Using the US postal address locator geo-database and branch addresses from the Statement of deposits, I create a national-level panel of physical branches that allows me to track every unique bank and branch-location pair over the last two decades. I can thus separate instances of physical closures from bank ownership changes. I re-examine the results of Table 3 under the following framework:

$$log(y_{i,t}^{minority}) = \alpha_i + \gamma_{c,t} + \beta_1 \mathbf{Treat}_i \cdot \mathbf{Post}_t \cdot \mathbf{C}_i + \beta_2 X_{i,t-1} + \varepsilon_{i,t}, \tag{7}$$

Here the indicator $\mathbf{C}_i$ is an indicator variable that identifies tracts that experience MDI branch-closures and MDI branch ownership-change. I present my findings in Table 4. Odd-numbered columns present results in case of physical MDI branch closures, while even-numbered columns present the results where branch ownership changes hands. Average of columns one (1) and two (2) is similar as the coefficient in column two (2) of Table 3. Under both IV and difference and differences specifications, the branch closures sub-sample has fewer minority mortgage originations (about twice as less) compared to the branch ownership change sub-sample. I also present the coefficients graphically in Figure 9. In this figure, I plot the year-wise coefficients around MDI-CB mergers. As can be visually inferred, the decline is observed more acutely in the case of branch closures.

An alternative hypothesis can be that when MDI is acquired by a community bank, the consolidated bank should no longer have an aggressive (and board-mandated) minority lending target. Consequently, minority application denials as a fraction of total denials would be higher in the ownership-change sub-sample, indicating that MDIs indeed go above and beyond in that they approve loans to marginalized borrowers whose applications would have been otherwise denied by a non-MDI bank. To test this, I use the HMDA loan registry database to obtain information on to minority application denials. Application denials rate results are presented in columns four (5) through eight (8).

I do not find conclusive evidence supporting this hypothesis. The coefficient are similar in the both the cases and a closer inspection of coefficients around mergers (see Figure 10) do not provide any conclusive trends. Overall, these results suggest that the disruptions in MDI banking relationships rather than a corporate strategy shift in form of increased denials are reponsible for the observed credit decline.

6 MDI's effect on minority home-ownership

Previous sections estimated the impact of MDI bank presence at a census tract level. In this section, I test whether the credit supply gap at small geographical level can aggregate to cause a detrimental impact on aggregate minority homeownership. Testing for minority homeownership is also an important as owning a home is the most important contributor to gaining household wealth (Wainer and Zabel (2020), Grinstein-Weiss et al. (2013)). I perform two sets of aggregate tests. For my first aggregate test, I use data from 1-year 1% ACS surveys ranging from 2001-2019 and directly measure the impact of increase of county year level deposits share of the *treated* tracts on minority homeownership percentage. I formally estimate the following model:

$$\mathcal{M}_{c,t} = \alpha_c + \gamma_{m,t} + \beta_1 \mathcal{S}_{c,t-1} + \beta_1 X_{c,t-1} + \varepsilon_{c,t}, \tag{8}$$

The dependent variable $\mathcal{M}_{c,t}$ is percentage minority home-ownership in year t in a county c. It calculated at a county level by aggregating more than 51 million individual records with information on homeownership and race using appropriate person weight from the IPUMS-USA 1% database (Ruggles et al. (2018)). The main explanatory variable is $\mathcal{S}_{c,t-1}$, which is the county year level share of *treated* tracts (tracts that experience an MDI-CB merger). $X_{c,t-1}$ is a set lagged county-level controls include the number of households(in '000s), minority percentage, county-MSA family income ratio, log of county deposits, Herfindahl Index, number of branches, log of county GDP and county housing price index. α_c and $\gamma_{m,t}$ represent county and MSA-year fixed effects respectively. The results are presented in Table 5.

For every 1% increase in the market share of the treated tracts, the minority homeownership percentage $\mathcal{M}_{c,t}$ by about 3% in that county as seen in Column (1) of Table 5. These results are much higher in tracts belonging to the principal central city of a metropolitan area. To put these findings into perspective, according to the American Housing Survey data[21], the racial homeownership gap in 2019 was at its peak at about 31.2%. By one es-

[21] https://www.census.gov/programs-surveys/ahs/data.html

timate[22], about 17% (or 5.3% of the total) of the homeownership gap can be attributed to unexplained reasons beyond income, marital status and credit scores. By these estimates, access to minority-owned banks can explain about half of the unexplained portion of the homeownership gap.

For my second county-level test, I use a matched sample of the Current Population Survey. I make use of the longitudinal design of the CPS allows me to track the responses of the same survey resident across the two consecutive survey years (Rivera Drew et al. (2014)). This allows me to measure the transition probability of survey residents to move from renting a home in the previous year to buying a home in the current year. To explain the role of MDIs on homeownership transition probability, I aggregate the deposit share of the treated tracts to a county level and use it to explain this transition probability. Formally, I estimate the following model:

$$(\mathcal{O}_{h,c,t-1,t} = 1) = \alpha_c + \gamma_{m,t} + \beta_1 \mathcal{S}_{c,t-1} + \beta_2 \theta_{h,c,t-1} + \beta_2 X_{c,t-1} + \varepsilon_{c,t} \tag{9}$$

The dependent variable ($\mathcal{O}_{h,c,t-1,t} = 1$) is the probability of household h in county c moving from not owning a home in year $t-1$ to owning one in the year t. The main explanatory variable is $\mathcal{S}_{c,t-1}$, which is the county-year level deposits share of the *treated* tracts (tracts that experience an MDI-CB merger). $\theta_{h,c,t-1}$ is a set of lagged individual-level controls, including gender, age, education, migration, marital status, race, and family income. $X_{c,t-1}$ is a set lagged county-level controls including the number of households(in '000s), minority percentage, county-MSA family income ratio, log of county deposits, Herfindahl Index, number of branches, log of county GDP and county housing price index. Standard errors are clustered at the county level. α_c and $\gamma_{m,t}$ represent county and MSA-year fixed effects respectively. Results are presented in Table 6. For every 1% increase in the market share of the treated tracts, the probability of a minority household making a transaction from renting to owning decreases by 3.25% (Column (1)). As in the previous aggregate test, the

[22] https://www.urban.org/urban-wire/breaking-down-black-white-homeownership-gap

results are more pronounced in tracts belonging to the principal central city of a metropolitan area.

7 Additional tests and robustness

In this section, I report the results of additional tests that lend credence to the results established in the previous sections.

7.1 Does profitability explain MDI-CB Mergers?

To the extent the CRA intensity instrument does not control for some local demand shocks that impact MDIs relatively more adversely, the CRA intensity instrument could capture the effect of mergers that occurred due to near failure of some MDIs and not for reasons attributed to CRA. In general, the effect is through banks' plummeting pre-merger profitability. Figure 7 plots the profitability of both the MDIs that merged with other MDIs and those that merged with community banks in the years leading up to the merger. Here, *profitability* is defined as net loss to average loans and leases. In other words, loss per dollar lent. As the figure confirms, the profitability of those MDIs that merged with community banks was not abnormally high in the years preceding the merger. On the contrary, profitability seems to have played a part in MDI-MDI mergers. In an untabulated non-result, I find no significance if I instrument the probability of treatment with the deposits-weighted 2006 real estate charge-off rates.

7.2 Alternative IV

Table 7 presents the baseline results under an alternative IV specification. Here, the external IV is created by first calculating the external CRA pressure given by:

$$\mathfrak{B}'_{b,t} = \sum_i \overline{\mathcal{C}}_{-i,t} \times \mathfrak{S}_{b,-i,t} \tag{10}$$

For bank b operating in a tract i, $\mathfrak{B}'_{b,t}$ is the average CRA intensity of all the tracts that the bank operates in, excluding the impact of current tract. Using this once removed bank level CRA intensity, the alternative instrument is calculated as:

$$\mathcal{C}'_{i,t} = \sum_b \mathcal{S}_{b,i,t} \times \frac{\mathfrak{B}'_{b,t}}{\mathcal{R}_{i,t}} \tag{11}$$

Aggregating the IV in this manner is a trade-off that reduces the impact of CRA but improves disassociation between the external instrument and local economic conditions. In the case of the preferred specification, IV captures a co-variate that can predict MDI community banking merger as many banks operating in the same tracts are undergoing CRA exams. In the once removed alternative specification, the banks operating in the same tract are still undergoing the CRA exam; however, the effect of the current tract importance vis-a-vis those exams is once removed. The correlation between the two IVs is 0.8, providing a sense of filtration achieved via aggregating in the manner above. The slope coefficient of -0.37 in column 4 of Table 7 columns is on the expected line, only slightly attenuated as the main difference is due to removing the effects of those banks that are *highly dependent* on the local area's economy. Such attenuation is expected to be smaller since banks are unlikely to have a very high percentage of their *overall deposits* in a single tract. Nevertheless, the results in this section should be interpreted as less prone to the effect of local economic factors.

7.3 Geographic diversity of MDI impact

Table 8 provides results of a sub-sample analysis using area classification scheme from the National Center for Health Statistics (NCHS, both the 2016 and the 2013 vintage). Since most MDIs are based in large metro the effects should mostly concentrated in large metro (more than 1 million Population). Within a large metro, the impact of MDI losses are much more strongly felt for minorities residing in central city neighborhoods compared to suburbs (See column 5 of Table 5 Table 6).

8 Conclusion

Financial inclusion is an important societal goal. Besides equality in education and health, true inclusion also entails equal access to financial services. Vast improvements in computing technology have rendered credit markets less informational opaque; however, these markets remain far from being frictionless. Consequently, the multiplier effects of credit markets are not evident in the broader asset markets, and staggering levels of wealth and income inequality persist. This paper studied if a mechanism based on re-empowering communities to perform essential functions well presents a viable solution.

MDIs are examples of a fruitful symbiotic relationship between the markets, the state, and the community. In this paper, I attempt to quantify their impact on the local economy. I find that a significant and persistent minority credit supply gap results when neighborhoods lose the presence of local minority-owned banks. I take steps to ensure that the documented effects are not attributed to fluctuations in local credit demand and establish a potential channel for the decline. I also estimate that MDIs matter significantly in reducing the homeownership gap. These benefits are not without costs. MDIs are relatively inefficiently run banks and prone to failures.

Therefore, promoting the long-term viability of the MDI ecosystem makes for a crucial policy-making goal. For example, tax holidays dedicated to minority bank investments or benefits in terms of regulatory ratios would be two steps in the right direction. For future research, whether technology enhances the delivery of mission-driven capital or leads to mission drift is a promising direction.

References

Agarwal, S., E. Benmelech, N. Bergman, and A. Seru. 2012. Did the Community Reinvestment Act (CRA) lead to risky lending? Tech. rep., National Bureau of Economic Research.

Allen, F., E. Carletti, R. Cull, J. Q. Qian, L. Senbet, and P. Valenzuela. 2021. Improving access to banking: Evidence from Kenya. *Review of Finance* 25:403–447.

Argyle, B., T. D. Nadauld, and C. Palmer. 2020. Real effects of search frictions in consumer credit markets. Tech. rep., National Bureau of Economic Research.

Banerjee, A., E. Duflo, R. Glennerster, and C. Kinnan. 2015. The miracle of microfinance? Evidence from a randomized evaluation. *American Economic Journal: Applied Economics* 7:22–53.

Barth, J., A. Betru, C. Lee, and M. Brigida. 2018. Minority-Owned Depository Institutions: A Market Overview.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace. 2021. Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics* .

Begley, T. A., and A. Purnanandam. 2021. Color and credit: Race, regulation, and the quality of financial services. *Journal of Financial Economics* 141:48–65.

Bhutta, N. 2011. The community reinvestment act and mortgage lending to lower income borrowers and neighborhoods. *The Journal of Law and Economics* 54:953–983.

Boot, A. W., and A. V. Thakor. 2000. Can relationship banking survive competition? *The Journal of Finance* 55:679–713.

Bord, V. M. 2017. Bank consolidation and financial inclusion: The adverse effects of bank mergers on depositors. *Unpublished Manuscript, Harvard University* .

Bostic, R. W., and H. Lee. 2017. Small business lending under the Community Reinvestment Act. *Cityscape* 19:63–84.

Breitenstein, E. C., K. Chu, K. Kalser, and E. W. Robbins. 2014. Minority depository institutions: Structure, performance, and social impact. *FDIC Quarterly* 8.

Burgess, R., and R. Pande. 2005. Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review* 95:780–795.

Card, D. 2001. Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica* 69:1127–1160.

Chakraborty, I., V. Chhaochharia, R. Hai, and P. Vatsa. 2020. Returns to community lending. *University of Miami Business School Research Paper* .

Degryse, H., N. Masschelein, and J. Mitchell. 2011. Staying, dropping, or switching: the impacts of bank mergers on small firms. *The Review of Financial Studies* 24:1102–1140.

Diamond, D. W. 1991. Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of political Economy* 99:689–721.

Drexler, A., and A. Schoar. 2014. Do relationships matter? Evidence from loan officer turnover. *Management Science* 60:2722–2736.

Edmonds, J. E., and S. H. Robicheaux. 2007. Minority Owned Community Banks: 1995-2004. *Academy of Banking Studies Journal* 6.

Fairlie, R. W., A. Robb, and D. T. Robinson. 2020. Black and white: Access to capital among minority-owned startups. Tech. rep., National Bureau of Economic Research.

Fisman, R., D. Paravisini, and V. Vig. 2017. Cultural proximity and loan outcomes. *American Economic Review* 107:457–92.

Garmaise, M. J., and T. J. Moskowitz. 2006. Bank mergers and crime: The real and social effects of credit market competition. *the Journal of Finance* 61:495–538.

Gilje, E. P., E. Loutskina, and P. E. Strahan. 2016. Exporting liquidity: Branch banking and financial integration. *The Journal of Finance* 71:1159–1184.

Grinstein-Weiss, M., C. Key, S. Guo, Y. H. Yeo, and K. Holub. 2013. Homeownership and wealth among low-and moderate-income households. *Housing Policy Debate* 23:259–279.

Haurin, D. R., C. E. Herbert, and S. S. Rosenthal. 2007. Homeownership gaps among low-income and minority households. *Cityscape* pp. 5–51.

Karolyi, S. A. 2018. Personal lending relationships. *The Journal of Finance* 73:5–49.

Kowalik, M., T. Davig, C. S. Morris, K. Regehr, et al. 2015. Bank consolidation and merger activity following the crisis. *Federal Reserve Bank of Kansas City Economic Review* 100:31–49.

Nguyen, H.-L. Q. 2019. Are credit markets still local? Evidence from bank branch closings. *American Economic Journal: Applied Economics* 11:1–32.

Okonkwo, V. 2003. Analysis of the portfolio behavior of black-owned commercial banks. *Journal of Academy of Business and Economics* 1.

Petersen, M. A., and R. G. Rajan. 1994. The benefits of lending relationships: Evidence from small business data. *The journal of finance* 49:3–37.

Price, D. A., et al. 1990. Minority-owned banks: History and trends. *Economic Commentary* July 1, 1990:1–6.

Reid, C., E. Seidman, M. Willis, L. Ding, J. Silver, and J. Ratcliffe. 2013. Debunking the CRA myth–Again. *UNC Center for Community Capital Working Paper (www. ccc. unc. edu/abstracts/debunkingCRAMyth. php)* .

Rivera Drew, J. A., S. Flood, and J. R. Warren. 2014. Making full use of the longitudinal design of the Current Population Survey: Methods for linking records across 16 months\m {1}. *Journal of economic and social measurement* 39:121–144.

Ruggles, S., S. Flood, R. Goeken, J. Grover, E. Meyer, J. Pacas, and M. Sobek. 2018. Ipums usa: Version 8.0 [dataset]. *Minneapolis, MN: IPUMS* 10:D010.

Saadi, V. 2020. Role of the community reinvestment act in mortgage supply and the US housing boom. *The Review of Financial Studies* 33:5288–5332.

Toussaint-Comeau, M., and R. Newberger. 2017. Minority-owned banks and their primary local market areas. *Economic Perspectives* 4:1–31.

Wainer, A., and J. Zabel. 2020. Homeownership and wealth accumulation for low-income households. *Journal of Housing Economics* 47:101624.

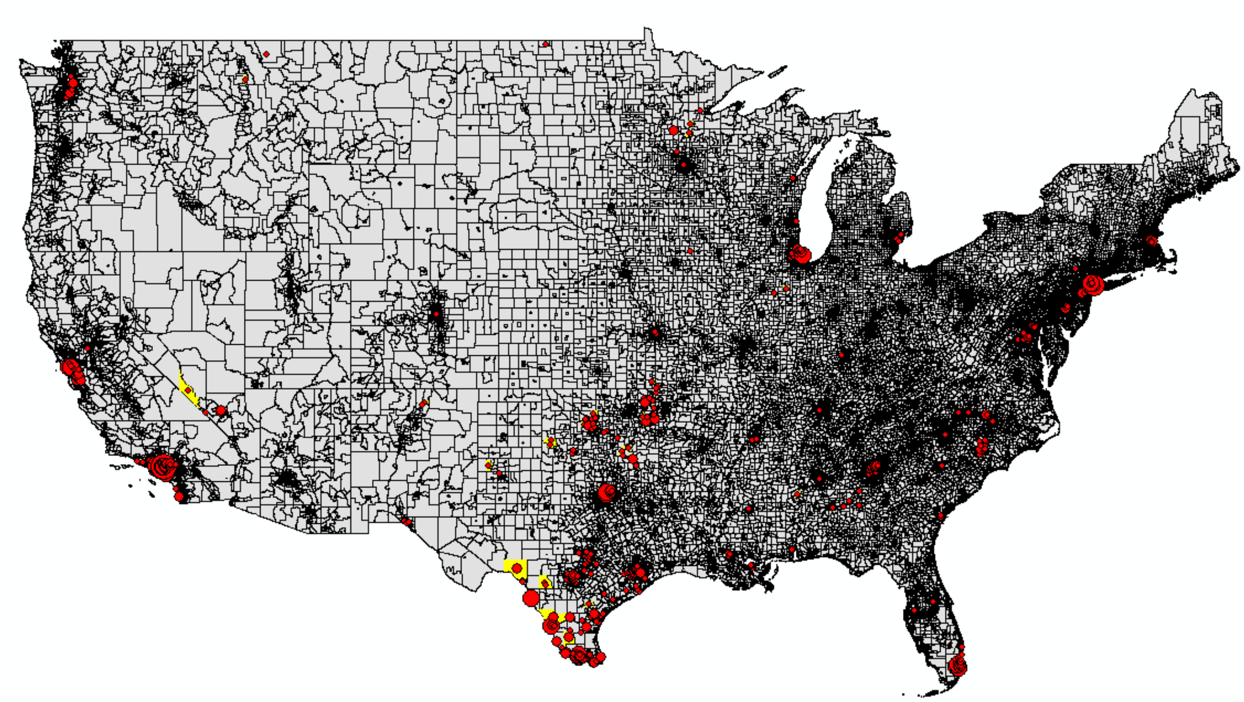
Windmeijer, F. A., and J. M. Santos Silva. 1997. Endogeneity in count data models: an application to demand for health care. *Journal of applied econometrics* 12:281–294.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data.* MIT press.

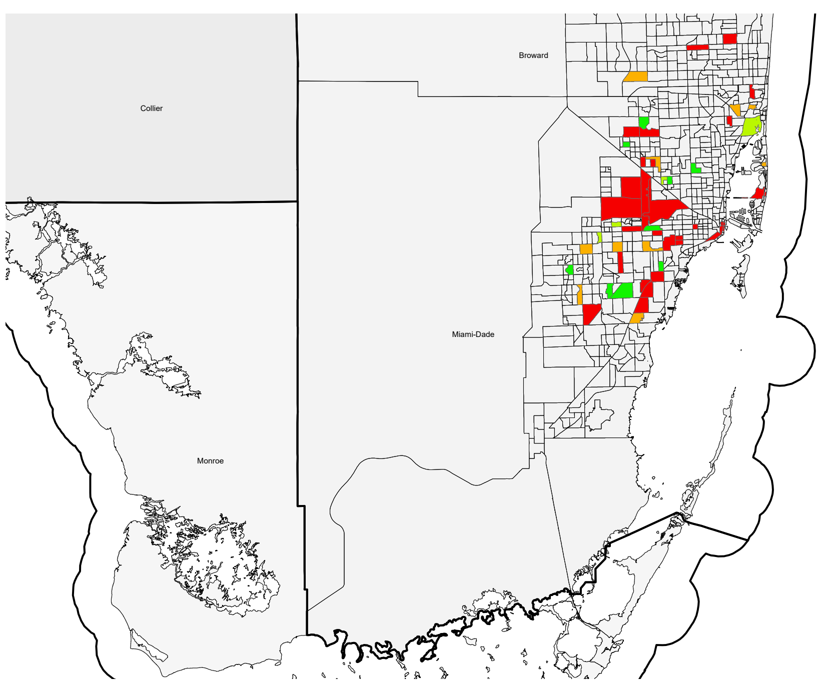
Zinman, J. 2002. *The efficacy and efficiency of credit market interventions: Evidence from the Community Reinvestment Act.* Joint Center for Housing Studies of Harvard University.

Figure 1: Geographical presence of MDIs in US census tracts

This figure presents the geographical location of MDIs in census tracts of contiguous United States (a) and in the Miami metropolitan area for reference in (b). Yellow colored tracts represent up to 25% deposit share, red tracts between 25% and 50% while blue tracts represent between 75% to 100% deposit share. Source: Author's calculation, ArcGIS, Summary of Deposits



(a)



(b)

Figure 2: Difference in Differences around MDI mergers

This figure plots the coefficients of the following model:

$$log(y_{i,t}^{minority}) = \alpha_i + \gamma_{c,t} + \beta_t \sum_{\tau} \mathbf{Treat}_i \cdot \mathbf{I}_{T=t} + \beta_2 X_{i,t-1} + \varepsilon_{i,t},$$

Y-axis represents level of mortgage origination to minorities, $y_{i,t}^{minority}$ in \$ millions, defined as the natural logarithm of amount of mortgage origination to applicants of Asian, African-American, Native American and Hispanic communities for purchase of owner occupied homes in a census tract i in a year t. X-axis represents the years relative to year of bank-merger denoted by 0. $\mathbf{Treat}_i$ is an indicator variable that takes on a value of 1 if census tract i experiences an MDI-Community bank merger. Control tracts are those where MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated tracts ($\mathbf{Treated}_i$) with with dummies for years relative to the year of bank-merger ($\mathbf{I}_{T=t}$). All coefficients are normalized relative to the year prior to the merger event. Standard errors are clustered at the county level. All continuous variables are winsorized at 99%. Model also includes $\gamma_{c,t}$ fixed effects, denoting that the comparison is controlling for within county-year variation.

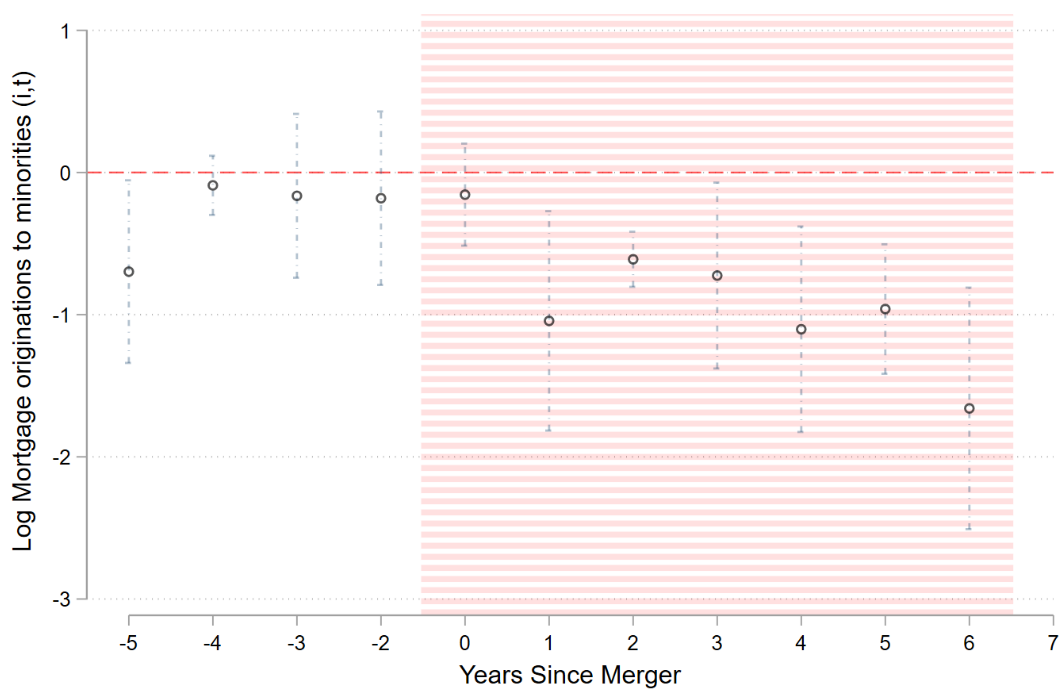
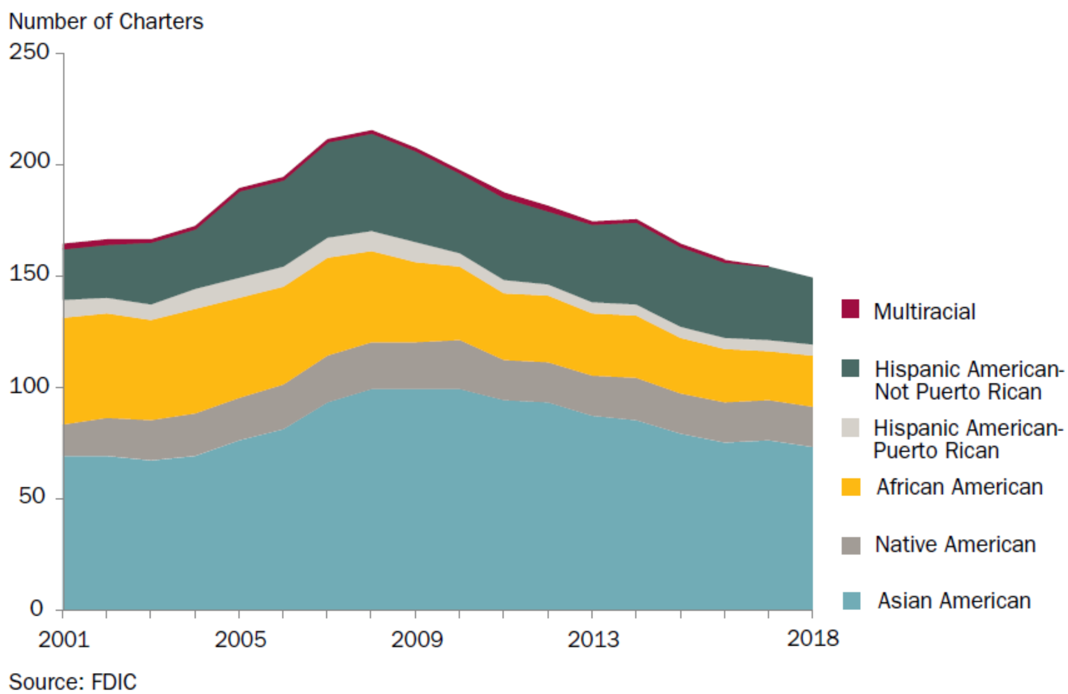


Figure 3: Number of MDI charters by type

This figures presents the number of MDI charters by MDI minority type from 2001 through 2018. Source - FDIC report



https://www.fdic.gov/regulations/resources/minority/2019-mdi-study/full.pdf

Figure 4: Minority mortgage lending - MDI presence

This figure plots the predictive margins for the following model:

$$
\begin{aligned}
log(y_{i,t}^{minority}) = \alpha + \beta_1 z\mathcal{S}_{i,t} + \beta_2 z\mathcal{R}_{i,t} + \beta_3 z\mathcal{M}_{i,t} + \beta_4(z\mathcal{S}_{i,t} \times z\mathcal{R}_{i,t}) + \\
\beta_5(z\mathcal{R}_{i,t} \times z\mathcal{M}_{i,t}) + \beta_6(z\mathcal{M}_{i,t} \times z\mathcal{S}_{i,t}) + \\
\beta_7(z\mathcal{S}_{i,t} \times z\mathcal{R}_{i,t} \times z\mathcal{M}_{i,t}) + \beta_8 X_{i,t-1} + \beta_{i,t}(i \cdot t) + \gamma_i + \theta_{c,t} + \varepsilon_{i,t},
\end{aligned}
$$

$z\mathcal{S}_{i,t}$, $z\mathcal{R}_{i,t}$ and $z\mathcal{M}_{i,t}$ respectively represent standardized values of MDI deposit share, tract-MSA family income ratio and minority percentage. Lagged tract level controls include number of households(in '000s), minority percentage, tract-MSA family income ratio, Herfindahl Index and number of branches in a tract. Y-axis represents change in log of mortgage origination to minorities, $y_{i,t}^{minority}$, defined as amount of mortgage origination to applicants of Asian, African-American, Native American and Hispanic communities for purchase of owner occupied homes in a census tract i in a year t. Standard errors are clustered at a tract level. X-axis represents change in MDI deposit share. All continuous variables are winsorized at 99%.

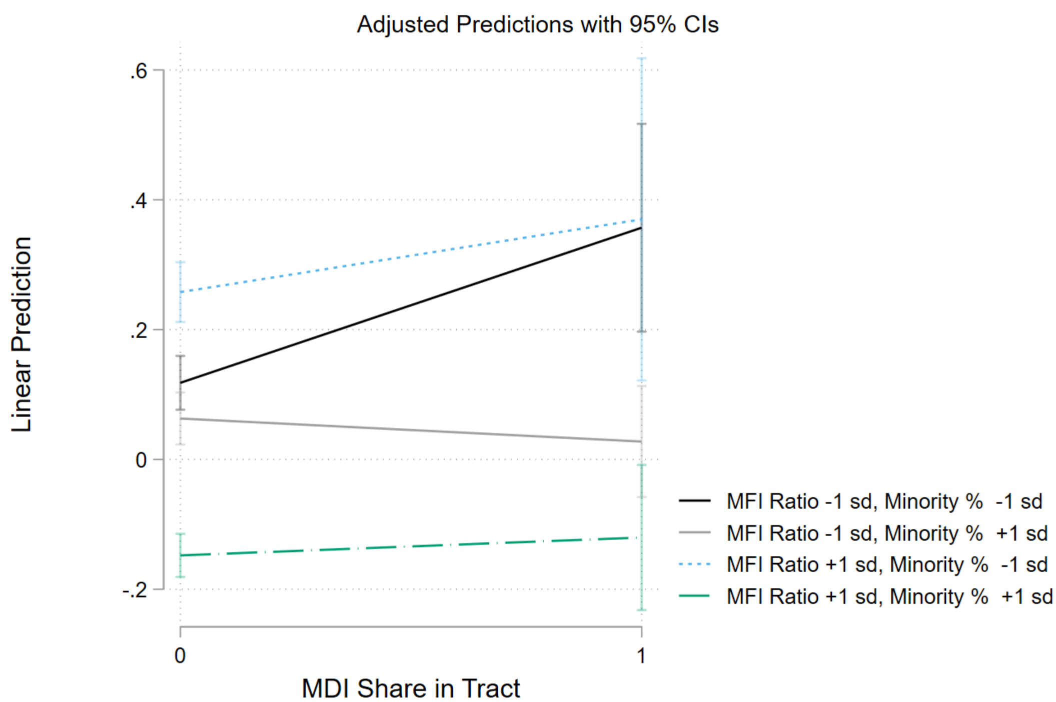


Figure 5: Acquisitions by MDI acquirers within 5 years of MDI acquisition

This figure plots the numbers of other acquisitions made by acquirers of MDIs within 5 years of their MDI acquisition. Blue bars represent community bank acquirers of MDIs, orange colored bars represent

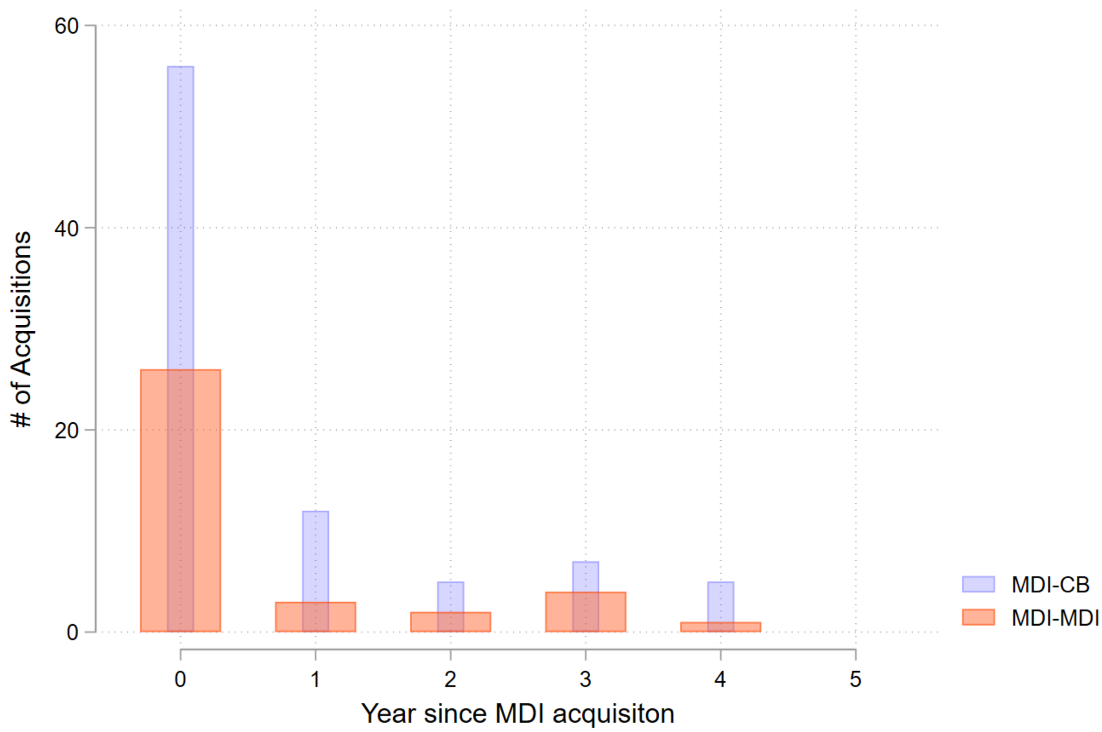


Figure 6: Change in Acquirer CRA intensity

This figure plots the change in CRA intensity faced by the acquiring banks, calculated as per Eqaution 5, in years leading up to the MDI mergers. Y-axis represents the y-o-y change in CRA intensity measured at a bank level for the acquiring banks against years leading up to the MDI merger (X-axis). Red line represents a merger between an MDI and a community bank, grey line represents an MDI-MDI merger while the blue line represents a merger between two community banks

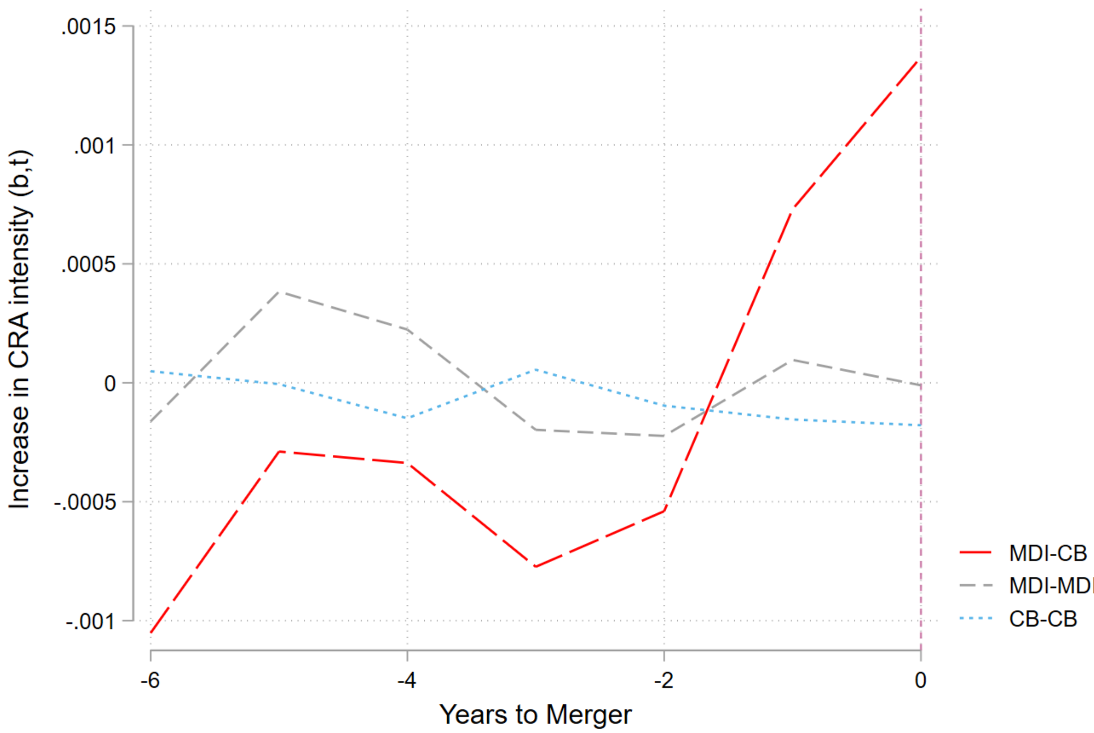


Figure 7: Profitability of MDIs prior to acquisitions

This figure plots the net loan losses as percentage of total loans and leases (Y-axis) in the years leading up to the MDI merger (X-axis) for the target banks. Solid black line represents a merger between an MDI and a community bank, grey line represents an MDI-MDI merger while the blue line represents a merger between two community banks

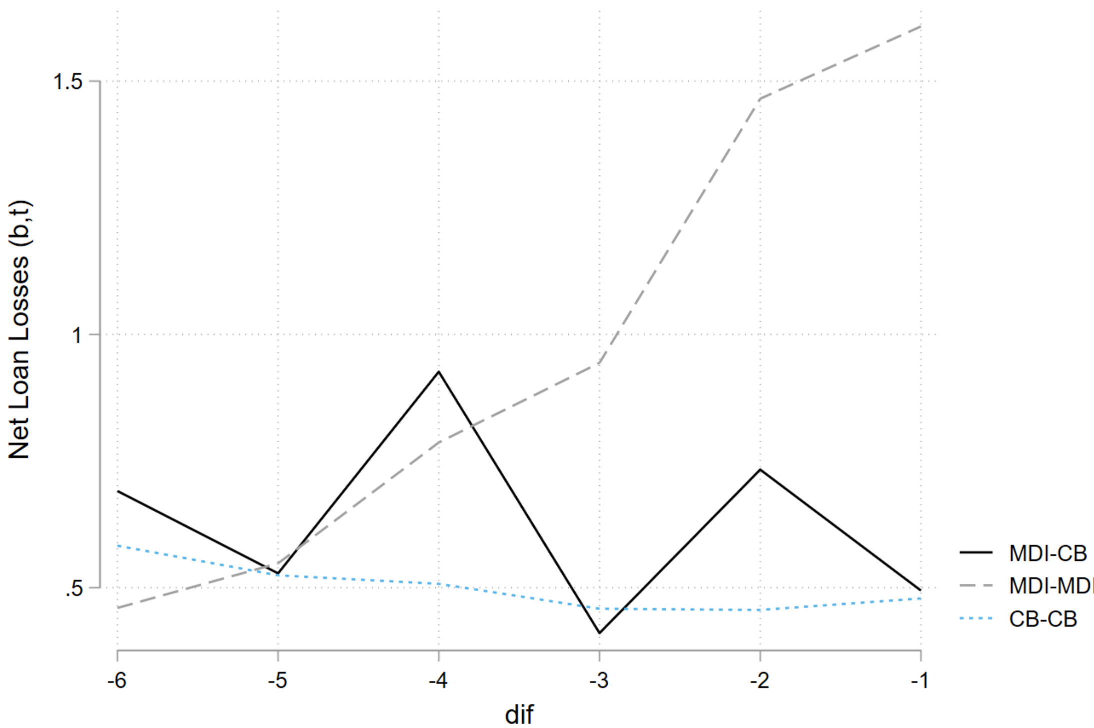
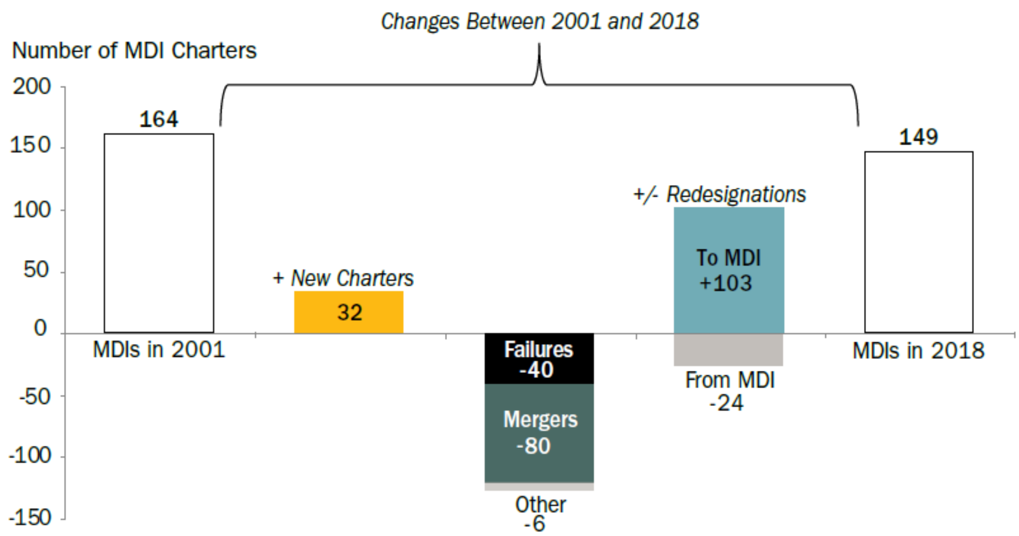


Figure 8: Structural changes of MDIs

This figures presents the structural changes in MDI charters from 2001-2018. Voluntary mergers are the greatest source of consolidation among MDIs over the last twenty years. Source - FDIC



Source: FDIC

https://www.fdic.gov/regulations/resources/minority/2019-mdi-study/full.pdf

Figure 9: Parallel Trends Originations - Closure Vs Change

This figure plots the coefficients of the following model:

$$log(y_{i,t}^{minority}) = \alpha_i + \gamma_{c,t} + \beta_1 \mathbf{Treat}_i \cdot \mathbf{Post}_t \cdot \mathbf{C}_i + \beta_2 X_{i,t-1} + \varepsilon_{i,t},$$

X-axis represents level of mortgage origination to minorities, $y_{i,t}^{minority}$ in \$ millions, defined as amount of mortgage origination to applicants of Asian, African-American, Native American and Hispanic communities for purchase of owner occupied homes in a census tract i in a year t. Y-axis represents the years relative to year of bank-merger denoted by the red vertical line. $\mathbf{Treat}_i$ is an indicator variable that takes on a value of 1 if census tract i experiences an MDI-Community bank merger. Control tracts are those where MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated tracts ($\mathbf{Treated}_i$) with with dummies for years relative to the year of bank-merger ($\mathbf{I}_{T=t}$) and ($\mathbf{C}_i$), an indicator variable that identifies tracts that experience MDI branch-closures and MDI branch ownership-change. All coefficients are normalized relative to the year prior to the merger event. Lagged tract level controls include number of households(in '000s), minority percentage, tract-MSA family income ratio, log of tract deposits, Herfindahl Index and number of branches in a tract. Standard errors are clustered at the county level. All continuous variables are winsorized at 99%

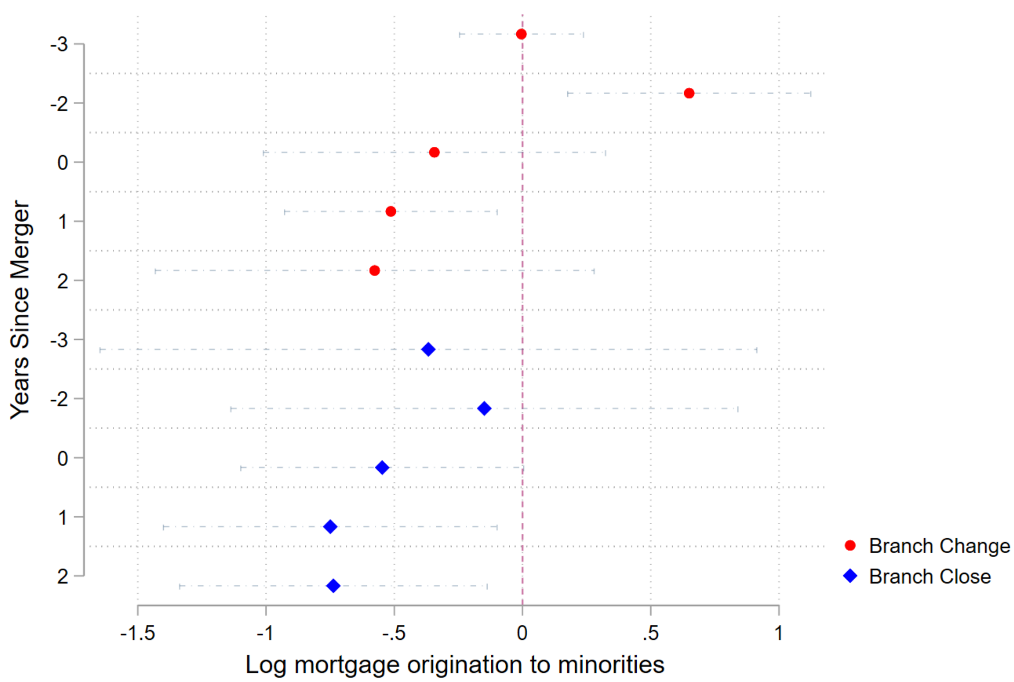


Figure 10: Parallel Trends Denials - Closure Vs Change

This figure plots the coefficients of the following model:

$$\mathcal{F}_{i,t}^{minority} = \alpha_i + \gamma_{c,t} + \beta_1 \mathbf{Treat}_i \cdot \mathbf{Post}_t \cdot \mathbf{C}_i + \beta_2 X_{i,t-1} + \varepsilon_{i,t},$$

Y-axis represents amount of minority mortgages denied as a fraction of total amount of mortgages denied. X-axis represents the years relative to year of bank-merger. $\mathbf{Treat}_i$ is an indicator variable that takes on a value of 1 if census tract i experiences an MDI-Community bank merger. Control tracts are those where MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated tracts ($\mathbf{Treated}_i$) with with dummies for years relative to the year of bank-merger ($\mathbf{I}_{T=t}$) and ($\mathbf{C}_i$), an indicator variable that identifies tracts that experience MDI branch-closures and MDI branch ownership-change. All coefficients are normalized relative to the year prior to the merger event. Lagged tract level controls include number of households(in '000s), minority percentage, tract-MSA family income ratio, log of tract deposits, Herfindahl Index and number of branches in a tract. Standard errors are clustered at the county level. All continuous variables are winsorized at 99%

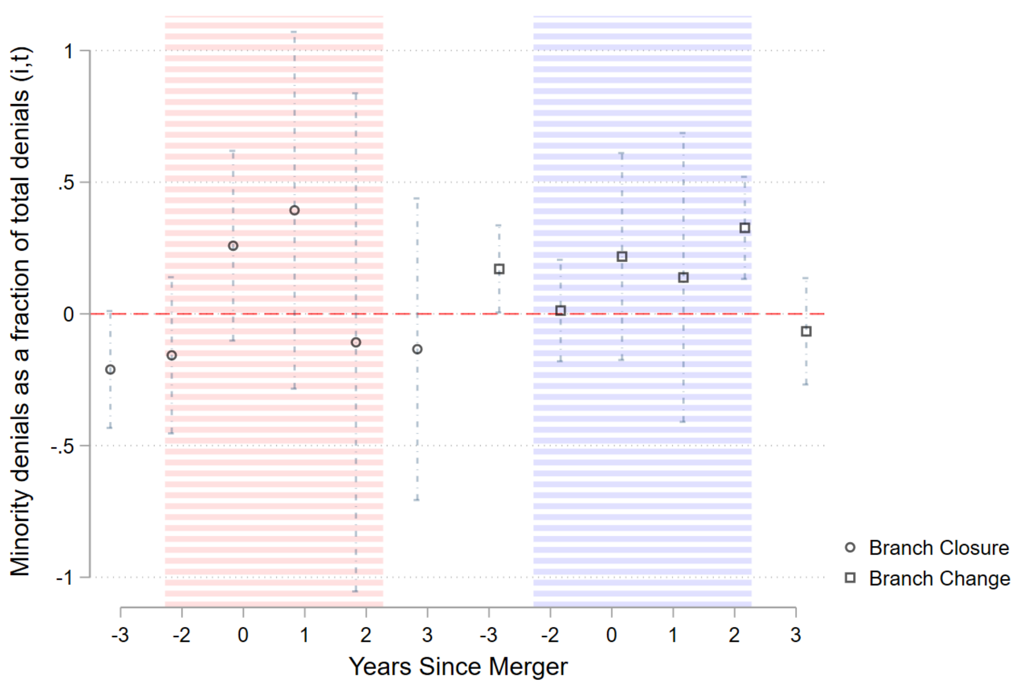


Table 1: Summary Statistics

This table presents the summary statistics of MDIs, the merger sample and MDI related HMDA lending. My sample period runs from 2001-2018. All variables are at an annual frequency. Panel A provides summary statistics at a bank-year level. Panel B compares summary statistics across MDI type. Table C presents summary statistics comparing MDIs and Community Banks across loan types

Panel A-I - Minority Depository Institutions								
Bank-Year	**Mean**	**Std. Dev**	**Median**	**Min**	**P25**	**P75**	**Max**	**N**
Balance Sheet items								
Total Assets ($ million)	1055.7	3427.2	173.4	4.7	82.2	464.5	41017.4	2843
Total Equity Capital ($ million)	114.2	367.4	18.8	-5.8	9.0	47.7	4401.9	2843
Core Deposits (% of Total Assets)	62.5	18.2	65.9	-33.8	53.7	75.3	96.9	2843
Short Term Non-Core Funding (% of Total Assets)	18.5	13.2	15.9	0.0	8.1	25.9	72.3	2843
Fully Insured Brokered Deposits (% of Avg. Assets)	3.9	7.7	0.2	0.0	0.0	4.5	59.7	2843
Net Loans and Leases (% of Total Assets)	64.7	15.2	67.6	0.0	57.1	75.6	95.4	2843
U.S. Treasury and Agency Securities ($ millions)	189.9	773.9	15.3	0.0	5.1	52.3	11715.0	2843
Fixed Assets (% of avg. assets)	1.8	1.7	1.3	0.0	0.6	2.5	19.4	2843
Held to maturity securities (% of avg. assets)	1.7	5.9	0.0	0.0	0.0	0.5	75.1	2843
Concentration of Credit								
Real estate loans ($ Million)	510.6	309.6	492.3	-5068.5	350.6	621.9	5746.9	2842
Commercial and industrial loans ($ Million)	88.9	86.5	67.7	-554.5	32.6	119.7	910.5	2842
Non-farm non residential loans ($ Million)	279.8	221.8	240.4	-2401.2	142.3	379.6	3773.3	2842
Construction and development loans ($ Million)	47.5	59.0	30.1	-232.1	8.5	63.5	625.6	2842
1-4 family residdential loans ($ Million)	135.2	167.0	96.6	-2249.8	29.6	186.0	3220.1	2842
Multifamily home loans ($ Millionl)	41.3	81.5	20.0	-185.3	4.2	48.0	1159.5	2842
Income Statement items								
Interest income (% of assets)	5.3	7.0	5.0	1.0	4.3	5.9	373.7	2843
Interest expense (% of assets)	1.4	1.4	1.1	0.0	0.6	1.9	51.1	2843
Provision for Loan & Lease Losses (% of assets)	0.5	1.0	0.2	-2.7	0.0	0.6	9.6	2843
Pretax Operating Income (% of assets)	-0.1	16.5	0.8	-846.9	-0.2	1.6	16.7	2843
Net income (% of assets)	-0.3	16.5	0.6	-846.9	-0.1	1.2	11.5	2843
Charge-offs less recoveries (% of assets)	0.6	1.2	0.2	-2.2	0.0	0.7	18.5	2843
Efficiency Ratio (%)	89.3	114.1	75.9	-745.3	61.1	93.1	4750.0	2,843

Panel A-II Community Banks								
Bank-Year	**Mean**	**Std. Dev**	**Median**	**Min**	**P25**	**P75**	**Max**	**N**
Balance Sheet Items								
Total Assets ($ million)	288.2	614.6	138.0	0.2	68.3	294.7	47364.8	101,770
Total Equity Capital ($ million)	30.4	67.6	14.5	-141.7	7.3	30.5	4407.1	101,770
Core Deposits (% of Total Assets)	72.0	22.0	74.4	-5624.0	65.6	81.2	99.0	101,770
Short Term Non-Core Funding (% of Total Assets)	11.0	8.8	9.1	0.0	4.2	15.7	87.9	101,770
Fully Insured Brokered Deposits (% of Avg. Assets)	2.1	9.7	0.0	0.0	0.0	1.4	2387.5	101,770
Net Loans and Leases (% of Total Assets)	62.6	15.4	64.9	0.0	53.3	74.1	96.9	101,770
U.S. Treasury and Agency Securities ($ millions)	41.1	116.4	16.1	0.0	6.1	38.9	7871.0	101,770
Fixed Assets (% of avg. assets)	1.8	1.4	1.5	0.0	0.8	2.5	22.7	101,770
Held to maturity securities (% of avg. assets)	3.3	8.5	0.0	0.0	0.0	1.6	86.1	101,770
Concentration of Credit								
Real estate loans (% total risk capital)	447.5	2413.6	428.9	-82064.0	289.2	567.5	750687.5	101,769
Commercial and industrial loans (% total risk capital)	85.0	327.8	67.4	-20636.7	36.1	112.0	91968.8	101,769
Non-farm non residential loans (% total risk capital)	154.9	920.6	128.0	-40809.5	55.9	218.1	277487.5	101,769
Construction and development loans (% total risk capital)	52.9	1185.6	26.7	-11477.0	7.4	63.7	376887.5	101,769
1-4 family residential loans (% total risk capital)	180.1	350.3	148.6	-21500.7	80.7	240.0	96312.5	101,769
Multifamily home loans (% total risk capital)	16.1	36.5	6.2	-1070.3	0.0	19.6	4401.5	101,769
Income statement items								
Interest income (% of assets)	5.0	1.8	4.9	0.0	4.1	5.8	321.4	101,770
Interest expense (% of assets)	1.3	1.0	1.1	0.0	0.5	1.9	141.6	101,770
Provision for Loan & Lease Losses (% of assets)	0.3	0.7	0.1	-7.6	0.0	0.3	81.6	101,770
Pretax Operating Income (% of assets)	1.0	4.1	1.2	-157.2	0.6	1.7	591.3	101,770
Net income (% of assets)	0.8	3.0	0.9	-190.4	0.5	1.3	467.2	101,770
Charge-offs less recoveries (% of assets)	0.4	3.1	0.1	-18.7	0.0	0.4	676.1	101,740
Efficiency Ratio (%)	74.1	355.3	68.2	-2459.5	59.2	79.1	112475.0	101,759

Table I: Summary Statistics - Mortgages ($ million) by MDI type

Bank-Year	Mean	Std. Dev	Median	Min	P25	P75	Max	N
Panel B-I								
Asian MDI								
Loan amount (Total)	38.3	123.3	3.0	0.0	0.7	19.7	1167.7	482
Loan amount LMI	6.4	17.7	0.4	0.0	0.0	3.3	148.2	482
Loan amount minority	25.2	74.5	2.4	0.0	0.4	11.9	933.7	482
Loan amount female	12.9	42.8	0.7	0.0	0.0	5.1	472.3	482
African-American MDI								
Loan amount (Total)	4.2	9.5	1.0	0.0	0.3	3.5	96.6	370
Loan amount LMI	0.8	1.5	0.2	0.0	0.0	0.8	9.8	370
Loan amount minority	2.1	3.9	0.6	0.0	0.2	2.1	30.9	370
Loan amount female	1.5	3.5	0.3	0.0	0.0	1.4	36.2	370
Hispanic MDI								
Loan amount (Total)	25.2	63.8	4.2	0.0	0.8	21.0	653.5	667
Loan amount LMI	3.4	12.0	0.5	0.0	0.0	2.5	168.6	667
Loan amount minority	21.2	58.0	3.6	0.0	0.5	17.5	640.0	667
Loan amount female	6.7	16.9	0.7	0.0	0.0	5.5	184.2	667
Native-American MDI								
Loan amount (Total)	4.4	11.3	0.8	0.0	0.2	3.2	98.0	232
Loan amount LMI	0.5	1.4	0.0	0.0	0.0	0.3	12.4	232
Loan amount minority	2.8	10.0	0.3	0.0	0.0	1.2	91.7	232
Loan amount female	1.6	4.8	0.2	0.0	0.0	0.9	41.0	232
Panel B-II								
Community Banks								
Loan amount (Total)	9.3	41.5	1.4	0.0	0.3	5.9	3629.1	88,391
Loan amount LMI	0.8	4.9	0.1	0.0	0.0	0.4	476.6	88,391
Loan amount minority	1.4	10.1	0.0	0.0	0.0	0.4	698.5	88,391
Loan amount female	2.1	11.0	0.2	0.0	0.0	1.1	1021.0	88,391

Table I: Summary Statistics - Mortgages ($ million) by loan type

Bank-Year	Mean	Std. Dev	Median	Min	P25	P75	Max	N
Panel C-I								
MDI								
Coventional - 1-4 Family	29.1	95.6	2.8	0.0	0.7	13.0	1167.7	1,097
FHA insured- 1-4 Family	19.4	27.7	5.6	0.0	1.6	30.4	164.1	211
VA insured- 1-4 Family	4.4	5.9	1.8	0.1	0.6	6.8	28.3	144
FSA/RHS - 1-4 Family	9.3	11.9	3.0	0.1	0.6	15.9	53.0	114
Coventional - Manufactured	0.3	0.6	0.1	0.0	0.1	0.3	6.0	128
FHA insured-Manufactured	1.1	2.1	0.3	0.1	0.1	0.8	7.2	22
Coventional - Multifamily	1.2	3.6	0.4	0.0	0.2	0.7	21.0	34
Panel C-II								
Community Bank								
Coventional - 1-4 Family	13.7	50.7	3.3	0.0	1.1	10.8	3629.1	46,529
FHA insured- 1-4 Family	16.4	60.7	3.8	0.0	1.0	12.3	3000.4	6,264
VA insured- 1-4 Family	9.1	32.7	1.7	0.0	0.5	5.6	734.8	5,357
FSA/RHS - 1-4 Family	3.2	6.5	1.2	0.0	0.4	3.2	153.4	5,868
Coventional - Manufactured	0.5	1.8	0.2	0.0	0.1	0.4	65.1	21,534
FHA insured- Manufactured	0.9	4.2	0.3	0.0	0.1	0.7	117.9	1,362
VA insured- Manufactured	0.5	1.0	0.2	0.0	0.1	0.4	9.2	624
FSA/RHS - 1-4 Manufactured	0.5	1.2	0.2	0.0	0.1	0.4	9.6	263
Coventional - Multifamily	0.6	2.9	0.2	0.0	0.1	0.4	65.1	579
FHA insured- Multifamily	0.2	0.1	0.2	0.1	0.1	0.3	0.4	9

Table I: Summary Statistics - Merger Sample

Panel C-III - Merger Sample								
Bank-Year	**Mean**	**Std. Dev**	**Median**	**Min**	**P25**	**P75**	**Max**	**N**
Control								
CRA Intensity	0.003	0.003	0.002	0.000	0.001	0.005	0.042	2240
Minority Loan Amount(000s)	5204	7415	2893	0	1240	6332	109016	2240
Households	1726	622	1706	460	1302	2087	4562	2240
MFI Ratio	102.5	49.3	92.3	23.8	69.6	122.8	358.7	2240
Total Bank Branches	5	4	3	1	2	6	29	2240
Total MDI Branches	1	2	1	0	0	2	11	2240
Total Deposits ('000s)	628,764	1,579,219	237,670	2,352	104,779	503,417	22,500,000	2240
Population	4,817	1,748	4,762	1,233	3,643	5,944	12,554	2240
Minority Percentage	69.99	26.04	78.03	3.04	49.34	93.66	100.00	2240
Treated								
CRA Intensity	0.003	0.003	0.002	0.000	0.000	0.004	0.024	596
Minority Loan Amount(000s)	6771	15823	2445	0	886	5870	217994	596
Households	1770	800	1617	0	1281	2227	4759	596
MFI Ratio	107.6	57.9	93.7	0.0	65.9	138.3	340.9	596
Total Bank Branches	5	4	3	1	2	6	27	596
Total MDI Branches	1	1	0	0	0	1	8	596
Total Deposits ('000s)	780,092	2,600,571	210,498	181	71,341	680,979	30,500,000	596
Population	4,875	2,061	4,896	59	3,390	5,958	10,783	596
Minority Percentage	53.6	29.0	53.9	4.1	29.0	80.0	98.8	596
Total								
CRA Intensity	0.003	0.003	0.002	0.000	0.001	0.005	0.042	2836
Minority Loan Amount(000s)	5533	9817	2815	0	1165	6288	217994	2836
Households	1735	663	1701	0	1288	2096	4759	2836
MFI Ratio	103.5	51.2	92.4	0.0	68.6	127.2	358.7	2836
Total Bank Branches	4.7	4.2	3.0	1.0	2.0	6.0	29.0	2836
Total MDI Branches	1.1	1.6	1.0	0.0	0.0	1.0	11.0	2836
Total Deposits ('000s)	660,566	1,841,962	229,568	181	96,322	521,156	30,500,000	2836
Population	4,829	1,818	4,771	59	3,596	5,945	12,554	2836
Minority Percentage	66.5	27.5	73.6	3.0	43.2	91.9	100.0	2836

Table 2: Mortgage originations to minorities and MDI presence in a census-tract

This table estimates the model in equation *1*. Dependent variable is the logarithm of total mortgage origination amount extended to minorities in a census tract-year. Main explanatory variables are the interactions of minority fraction with median family income relative to MSA family income(MFI fraction) and deposit share of MDIs in the tract. All specifications control for lagged tract level controls including number of households(in '000s), minority percentage, median family income relative to MSA family income(MFI fraction), Herfindahl Index and number of branches in a tract. Standard errors are in parentheses and are clustered at the tract level. All continuous variables are winsorized at 99%.

	Log mortgage origination to minorities			
	(1)	(2)	(3)	(4)
zMinority %	-0.1175***		-0.1526***	-0.1166***
	(0.02)		(0.02)	(0.02)
zMFI Ratio	-0.0170**	-0.0355***		-0.0180**
	(0.01)	(0.01)		(0.01)
zMinority % × zMFI Ratio	-0.0844***			-0.0869***
	(0.01)			(0.01)
zMDI Market Share		-0.0011	0.0109*	0.0099
		(0.00)	(0.01)	(0.01)
zMDI Market Share × zMFI Ratio		-0.0038		-0.0018
		(0.00)		(0.00)
zMDI Market Share × zMinority %			-0.0086***	-0.0103***
			(0.00)	(0.00)
zMDI Market Share × zMFI Ratio × zMinority %				0.0055**
				(0.00)
Controls	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Linear Time Trend	Yes	Yes	Yes	Yes
Observations	298,019	298,019	298,019	298,019
Adjusted R^2	0.8364	0.8361	0.8362	0.8365

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3: Difference in differences and IV estimation

This table estimates the model in Equation 7. Dependent variable is the log of mortgage origination to minorities. $\textbf{Treated}_i$ is an indicator variable that takes on a value of 1 if census tract i experiences an MDI-Community bank merger. Control tracts are those where MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated tracts with post merger dummy ($\textbf{Post}_t$). All coefficients are normalized relative to the year prior to the merger event. Columns (1) and (2) provided the difference in differences results, columns (3) and (4) provide parallel trends assumption. Lagged tract level controls include number of households(in '000s), minority percentage, tract-MSA family income ratio, log of tract deposits, Herfindahl Index, lagged dependent variable and the number of branches in a tract. Robust standard errors are clustered at the county level. All continuous variables are winsorized at 99%

	Mortgage originations to minorities			
	Dif-Dif	Dif-Dif	Reduced Form	IV
	(1)	(2)	(3)	(4)
Treated × Post	-0.2985	-0.3292***	-0.3422**	-0.3731**
	(0.19)	(0.09)	(0.15)	(0.14)
Controls	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
County-Year FE	No	Yes	Yes	Yes
Observations	2,351	1,706	1,277	1,706
Adjusted R^2	0.7359	0.8083	0.8354	0.8452
SW F Statistic	-	-	-	72.26

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4: Relationship Channel Vs Corporate Strategy Channel

This table estimates the model in Equation 7. Dependent variable is the log of mortgage origination to minorities. **Treated**$_i$ is an indicator variable that takes on a value of 1 if census tract i experiences an MDI-Community bank merger. Control tracts are those where MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated tracts with post merger dummy (**Post**$_t$). All coefficients are normalized relative to the year prior to the merger event. Odd-numbered columns provide the estimates for sub-sample of tracts that experienced branch closure following the merger. Even-numbered columns provide estimates for tracts where branch ownership changed. Lagged tract level controls include number of households(in '000s), minority percentage, tract-MSA family income ratio, log of tract deposits, Herfindahl Index, lagged dependent variable and the number of branches in a tract. Robust standard errors are clustered at the county level. All continuous variables are winsorized at 99%

	Mortgage originations to minorities				Mortgage denials to minorities			
	Dif-Dif		IV		Dif-Dif		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post × Closure	-0.5765***		-0.8730***		0.2583***		0.2319***	
	(0.07)		(0.21)		(0.09)		(0.07)	
Treated × Post × Change		-0.1880***		-0.4952***		0.2776***		0.3059***
		(0.07)		(0.11)		(0.09)		(0.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,560	1,560	1,521	1,521	1,391	1,391	1,391	1,391
Adjusted R^2	0.7995	0.7988	0.07435	0.07121	0.6752	0.6747	0.04072	0.03939

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: Minority Home-ownership Percentage - ACS - 1 yr

This table estimates the following model:

$$\mathcal{M}_{c,t} = \alpha_c + \gamma_{m,t} + \beta_1 \mathcal{S}_{c,t-1} + \beta_1 X_{c,t-1} + \varepsilon_{c,t},$$

The dependent variable $\mathcal{M}_{c,t}$ is percentage minority home-ownership in year t in a county c. The main explanatory variable is $\mathcal{S}_{c,t-1}$, which is the county year level share of *treated* tracts (tracts that experience an MDI-CB merger). $X_{c,t-1}$ is a set lagged county level controls include number of households(in '000s), minority percentage, county-MSA family income ratio, log of county deposits, Herfindahl Index, number of branches, log of county GDP and county housing price index. Standard errors are clustered at the county level. α_c and $\gamma_{m,t}$ represent county and MSA-year fixed effects respectively. All continuous variables are winsorized at 99%

	County Year - Percentage Minority Home-ownership					
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Share Treated	-2.9868***	-3.4168**	-58.2241***	-3.5308**	-18.2869***	-3.1233***
	(1.0927)	(1.3991)	(12.3109)	(1.4506)	(1.5873)	(0.5813)
County GDP	Yes	Yes	Yes	Yes	Yes	Yes
County HPI	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	No	Yes	No	Yes	Yes	Yes
MSA-Year FE	No	No	Yes	No	No	No
Observations	541	322	112	273	151	122
Adjusted R^2	0.9901	0.9918	0.9940	0.9882	0.9859	0.9894
Sub-sample	Full	Full	Full	Large Metro	Central City	Suburb

* p<0.10, ** p<0.05, *** p<0.01

Table 6: Household home-ownership transition probability

This table estimates the following model:

$$(\mathcal{O}_{h,c,t-1,t} = 1) = \alpha_c + \gamma_{m,t} + \beta_1 \mathcal{S}_{c,t-1} + \beta_2 \theta_{h,c,t-1} + \beta_2 X_{c,t-1} + \varepsilon_{c,t}$$

The dependent variable $(\mathcal{O}_{h,c,t-1,t} = 1)$ is the probability of household h in county c moving from not owning a home in year $t-1$ to owning one in the year t. The main explanatory variable is $\mathcal{S}_{c,t-1}$, which is the county year level share of *treated* tracts (tracts that experience an MDI-CB merger). $\theta_{h,c,t-1}$ is a set of lagged individual-level controls listed in the table below. $X_{c,t-1}$ is a set lagged county level controls include number of households(in '000s), minority percentage, county-MSA family income ratio, log of county deposits, Herfindahl Index, number of branches, log of county GDP and county housing price index. Standard errors are clustered at the county level. α_c and $\gamma_{m,t}$ represent county and MSA-year fixed effects respectively. All continuous variables are winsorized at 99%

	Household - Transition probability Home-ownership					
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Share Treated	-3.2573***	-2.6528***	-1.2107***	-1.2834***	-18.5707***	-10.3853***
	(0.8068)	(0.6764)	(0.3448)	(0.3603)	(6.5698)	(2.3928)
Log Age	Yes	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Migration	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	No	Yes
MSA FE	No	Yes	No	No	No	Yes
MSA-Year FE	No	No	Yes	Yes	Yes	No
Observations	57,014	57,014	57,010	49,960	29,369	9,013
Adjusted R^2	0.0103	0.0149	0.0207	0.0205	0.0355	0.0362
Sub-sample	Full	Full	Full	Large Metro	Central City	Suburb

* p<0.10, ** p<0.05, *** p<0.01

Table 7: Robustness I - Alternative IV

This table estimates the model in equation 7. Dependent variable is the log of mortgage origination to minorities. **Treated**$_i$ is an indicator variable that takes on a value of 1 if census tract i experiences an MDI-Community bank merger. Control tracts are those where MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated tracts with post merger dummy (**Post**$_t$). All coefficients are normalized relative to the year prior to the merger event. Columns (1) and (2) provided the difference in differences results, columns (3) and (4) provide parallel trends assumption. Lagged tract level controls include number of households(in '000s), minority percentage, tract-MSA family income ratio, log of tract deposits, Herfindahl Index, lagged dependent variable and the number of branches in a tract. Standard errors are clustered at the census-tract level in column (1) and at county level in columns (2) - (4). All continuous variables are winsorized at 99%

	Mortgage originations to minorities			
	Dif-Dif	Dif-Dif	Reduced Form	IV
	(1)	(2)	(3)	(4)
Treated × Post	-0.2985	-0.3292***	-0.4502**	-0.3724**
	(0.19)	(0.09)	(0.19)	(0.15)
Controls	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
County-Year FE	No	Yes	Yes	Yes
Observations	2,351	1,706	1,277	1,706
Adjusted R^2	0.7359	0.8083	0.8355	0.8374
SW F-Statistic	-	-	-	65.42

* p<0.10, ** p<0.05, *** p<0.01

Table 8: Robustness II - By Geography Type

This table estimates the model in equation 7. Dependent variable is the log of mortgage origination to minorities. **Treated**$_i$ is an indicator variable that takes on a value of 1 if census tract i experiences an MDI-Community bank merger. Control tracts are those where MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated tracts with post merger dummy (**Post**$_t$). All coefficients are normalized relative to the year prior to the merger event. Columns (1) and (2) provided the difference in differences results, columns (3) and (4) provide parallel trends assumption. Lagged tract level controls include number of households(in '000s), minority percentage, tract-MSA family income ratio, log of tract deposits, Herfindahl Index and number of branches in a tract. Standard errors are clustered at the census-tract level in column (1) and at county level in columns (2) - (4). All continuous variables are winsorized at 99%

	Mortgage originations to minorities			
	(1)	(2)	(3)	(4)
	Dif-Dif	Dif-Dif	Dif-Dif	IV
	(1)	(2)	(3)	(4)
Treated × Post	-0.2981***	0.6004	(.)	-0.3454**
	(0.09)	(0.34)	(.)	(0.15)
Controls	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
County-Year FE	Yes	No	No	Yes
Observations	1,365	234	413	1,365
Adjusted R^2	0.8018	0.7180	0.8310	0.8439
Sub-Sample	Large-Metro	Medium-Small Metro	Rural	Large-Metro

* p<0.10, ** p<0.05, *** p<0.01

Appendix: For review and online publication only

A MDIs - Definition, History and Geography

A.1 Definition

Enactment of the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA) (amended subsequently by Section 367 of the Dodd-Frank Act of 2010) formalized the concept of Minority Depository Institutions. Under section 308 of FIRREA, an MDI may be a federally insured depository institution for which (1) 51 percent or more of the voting stock is owned by minority individuals; or, after a 2002 amendment, (2) a majority of the board of directors is a minority and the community that the institution serves is predominantly minority. Ownership must be by U.S. citizens or permanent legal U.S. residents. The term "Minority" was defined in Section 308 of FIRREA to mean any "Black American, Asian American, Hispanic American, or Native American."

Election for an MDI status by a bank is voluntary. Once granted the MDI status, the institutions participate in FDIC's Minority Depository Institutions Program. The goal of the program is to preserve and promote minority ownership of participating institutions. To this end, the FDIC takes necessary steps such as providing technical assistance regarding regulatory compliance, FDIC policies, examination procedures, and help with risk management procedures. Importantly, FDIC attempts to preserve the minority character of failing MDIs during the resolution process.

Besides FDIC, the other regulators, namely the Federal Reserve System and the Office of Comptroller of Currency (OCC), have their own definitions of MDIs consistent with Section 308 of FIRREA. For my analysis, I combine MDI lists from all the three regulators (Toussaint-Comeau and Newberger (2017)) and collectively refer to them as MDIs.

A.2 Brief history

Minority-owned financial institutions have existed ever since 1866 (Price et al. (1990)). The period following the civil war saw the creation of many African American banks for the provision of credit to the newly freed African-American communities, especially in the antebellum South. At the time, these banks were the only source of financial services accessible to the African-American communities. By one estimate (Okonkwo (2003)), about 134 African-American-owned banks were operational between 1888 and 1934. However, most of these banks failed during the Great Depression, and by the late 1930s, only nine black-owned were left operational. Asian and Hispanic-owned minority banks, on the other hand, came into existence much later in the 1960s, and the first native American bank came into existence in the mid-1980s (Toussaint-Comeau and Newberger (2017)).

Following the Civil Rights Movement, MDIs grew strongly throughout the 1970s. One contributing factor was that under executives orders #11458 and #11635 signed by President Nixon, the Commerce and Treasury Departments established the Minority Bank Development Program (MBDP). The MDBP published the roaster of MDIs and encouraged both public and private organizations to engage with and use the services of minority banks. Consequently, eligible participants received deposits from Government agencies such as the Department of Housing and Urban Development (HUD) and the Department of Energy (DoE) (Price et al. (1990)). However, the Savings and Loans (S&L) crises of the 1980s affected the MDIs disproportionately more, and by 1988, 35 black-owned banks closed down due to the S&L crisis (Okonkwo (2003)).

During the 1990s, minority-owned banks increased in number, primarily due to increased numbers of "community" Asian (from 11 to 27) and Hispanic-owned banks (from 5 to 13). African-American community banks' growth remained flat during this period (Edmonds and Robicheaux (2007)). By 2001 there were 164 MDIs (via both the ownership and majority board criteria) operational, out of which 69 were Asian, 48 were

African-American, 31 were Hispanic, 2 were Mixed ethnicity, and 15 were Native American banks.

A.3 Present composition and structural changes

Over the last 20 years, the number and composition of MDIs have familiarly ebbed and flowed. The Great Recession and housing crisis were particularly severe on MDIs. Leading up to the 2008 financial crisis, the number of MDIs increased from 164 in 2001 to 215 in 2008, before declining to 149 as of December 31, 2018, see Figure 3. As of 2018, about half of all MDIs were Asian MDIs (73), 23% (35) were Hispanic American, 15% (23) were African American, and 12% (18) were Native American MDIs.

MDIs are inherently small-sized non-specialty banks having a local presence, with non-MDI community banks being their closest peers. Almost all MDIs (about 87%) qualify as community banks[23]. In terms of banking industry size, as of 2018, MDIs constituted only about 1.5% of the total banking assets, with a combined asset base of about $ 234 billion while they accounted for about 2.9% of the total number of bank charters. In contrast, TD Bank, the 10th largest US bank by size, alone has assets of about $ 360 billion. It is worth noting that even though during the last 20 years, the number of MDI charters has gone up and come down, their asset base has almost tripled from $84 billion in 2001 to $234 billion in 2018. Yet, MDI's share of total industry assets has remained about the same, i.e., about 1.5%.

Figure 8, depicts the major sources of structural changes for MDIs between 2001 and 2018. MDI re-designations and voluntary mergers were the biggest contributors to the structural changes in MDIs over the last two decades. In all, 103 institutions gained MDI status while 24 lost the MDI status between 2001 and 2018. Re-designations can occur, either due to the changes in ownership structure or a pre-qualified bank's formal request to be granted

[23] Refer to FDIC's community bank definition given in Figure C.3

the MDI designation. There were also 32 new charters, although there have not been any de novo MDI charters over the last ten years spanning 2009-2019. During the same period, there were 80 voluntary mergers of MDIs. Also, during 2001-2018, there were 40 MDI failures. These failed banks were absorbed in FDIC-assisted mergers (23 by MDIs and 15 by non-MDIs, and liquidation of 2 banks occurred via depositor payoffs).

A.4 Geographical presence and primary service areas

Figure 1-a shows the presence of MDI bank-branches across US census tracts in 2018. Southern California metros are home to 31 of the 73 Asian-owned MDIs. In contrast, Hispanic-American banks cluster around the Texas-Mexico border, south Florida, and Puerto Rico. Chicago, Richmond, and Atlanta Federal Reserve Districts are the main locations for African-American MDIs. In all, the top ten metropolitan areas account for about 66% of all MDI head offices. The figure also shows that MDI branches tend to cluster more prominently in the inner city neighborhoods (see, Figure 1-b).

As of 2018, MDI operated 1,524 branches spread over 82 MSAs, 251 counties, and 1,020 census tracts. Forty-two metro areas were the location for the head offices of 149 MDIs. Los Angeles (31), New York (14), and Miami (10) MSAs accounted for 40% of all MDI head offices. Of the 1,020 census tracts served by MDIs, 401 census tracts had a 100% deposit share of MDIs (MDI-only tracts). The average deposit share of MDI in a tract conditional on an MDI presence was 56%.

Over the entire sample period from 2001-2018, the Median Family Income (MFI) of the tracts where MDIs had a presence was 104% of the metro area MFI while the minority population percentage in these tracts was 73%. For MDI-only tracts, the tract to metro area MFI ratio was 103%, and the minority population in these tracts was as high as 85%. 40% of all tracts served by MDI were LMI (Low to Moderate Income) tracts in 2018, meaning their tract to metro MFI ratio was less than 80%. Among MDI-only tracts, more than half of the tracts were LMI tracts. In stark contrast, of the tracts served by non-MDI community banks, only 16% on an average classified as LMI tracts, and the percentage of the minority population in these tracts was 20%.

B Data

Table B.I: List of Main Databases

Following is the list of databases that I used in my analysis. Also indicated is the panel-level at which these data provide maximum granularity. Besides these databases, I used TIGER/Line Shapefiles for census boundaries and US Postal address locator Geo-database

Database name	Description	Level
Call Reports	Report of Condition and Income reports the balance-sheet,structure and income variables of banks on a quarterly basis	bank-quarter
SOD	The Summary of Deposits - geocoded using ArcGIS software -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	bank-tract-year
UBPR	The UBPR is an individual analysis of financial institutions that includes extensive comparisons to peer group performance.	bank-quarter
CRA	These reports summarize CRA small business lending information for individual institutions	bank-tract-year
HMDA	The Home Mortgage Disclosure Act (HMDA) requires financial institutions to maintain, report, and publicly disclose loan-level information about mortgages	bank-tract-year-race
MDI	The FDIC maintains a list and tracks the insured MDIs it supervises, i.e., state-chartered institutions that are not members of the Federal Reserve System (Federal Reserve), as well as MDIs that are supervised by the Office of the Comptroller of the Currency (OCC) and the Federal Reserve.	bank-year
CRA Exam	CRA ratings of financial institutions supervised by the Federal Reserve, Office of the Comptroller of the Currency, Federal Deposit Insurance Corporation, and/or Office of Thrift Supervision	bank-quarter
ACS	The American Community Survey (ACS) is an ongoing survey that provides vital information on a yearly basis about US and its people	person-county-year
CPS	The Current Population Survey (CPS) is the main source of labor force statistics for the United States. In the March supplement the	person-county-year

Table B.II: Definition and Sources of Main Variables

The main data sources are the CRA Database from FFIEC, the Summary of Deposits (SOD), Uniform Bank Performance Report (UBPR), the Current Population Survey(CPS), County Business Patterns (CBP), Quarterly Workforce Indicators(QWI), the American Community Survey (ACS), U.S. Bureau of Labor Statistics(BLS) and Small Area Income and Poverty Estimates (SAIPE)

Variable name	Description	Source
Minority	Defined as per Section 308 of FIRREA to mean "Black American, Asian American, Hispanic American, or Native American"	FFIEC
Minority Mortgage Lending	Amount of mortgage origination to minorities for purchase of owner occupied homes in a census tract i in a year t	HMDA
MFI Ratio	Ratio of a census tract's median annualized family income to either an MSA or MD median family income or a statewide non-metropolitan area median annualized family income	Census
CRA Intensity	Defined as per Equation 4	SOD,CRA Exams
Branch Closure	If the physical branch-location was an MDI branch for two consecutive years followed by physical closure	Branch-SOD
Branch Change	If the physical branch-location was an MDI branch for two consecutive years followed by change of owner-bank	Branch-SOD
Bank Deposits	Branch office deposits as of June 30 for all FDIC-insured institutions, including insured U.S. branches of foreign banks.	SOD
County GDP	Computed as the sum of compensation of employees (COMP), taxes on production and imports (TOPI) less subsidies (SUB), and gross operating surplus (GOS)	BEA
Profitability	*ubpre019* Gross loan and lease charge-off, less gross recoveries (includes allocated transfer risk reserve charge-off and recoveries), divided by average total loans and leases.	UBPR
Education	CPS variable EDUC99 reports the respondent's highest level of educational attainment. Respondents without high school diplomas were to indicate the highest school grade they had completed, while those with high school diplomas were to indicate the highest diploma or degree they had obtained.	CPS
County Deposits	Branch office deposits as of June 30 for all FDIC-insured institutions, including insured U.S. branches of foreign banks aggregated to county-year level	SOD
Home ownership	CPS variable OWNERSHP indicates whether the household rented or owned its housing unit. Households that acquired their unit with a mortgage or other lending arrangement were understood to "own" their unit even if they had not yet completed	CPS
Ownership Transition	Takes on the value of 1 if the variable ownershp, is not equal to '10' at year $t-1$ and equal to '10' at t and race is not '100'	CPS
Official Income	*offtotval* is the total family income used for replicating official poverty rates. offtotval treats primary families and related subfamilies within a given household as one family, in accordance with the official poverty guidelines.	CPS

Table continued.

	Panel B:Bank-Year	
Variable name	Description	Source
Total Real Estate Loans	*ubpre884* -Construction, land development and other land loans, closed-end loans secured by 1-4 family residential properties (first liens, junior liens, and revolving open-end loans), loans secured by farmland, loans secured by multifamily residential properties, and loans secured by non-farm non-residential properties divided by total risk-based capital.	UBPR
Cost of deposits	*ubpre116* - Interest on all interest-bearing deposits in domestic offices, interest-bearing foreign office deposits, demand notes (note balances) issued to the U.S. Treasury, other borrowed money, subordinated notes and debentures, and expense on federal funds purchased and securities sold under agreements to repurchase, interest expense on mortgage and capitalized leases divided by the average of the liabilities or funds that generated those expenses.	UBPR
Core deposits	*ubpre591* - Core deposits equals the sum of all transaction accounts + nontransaction money market deposit accounts + nontransaction other savings deposits (excludes MMDAs) + nontransaction time deposits of $250,000 and less - fully insured brokered deposits $250,000 and less.	UBPR
Total Equity	*ubpr3210* - Total bank equity capital from Call Report Schedule RC.	UBPR
Total Assets	*ubpr2170* - Total Assets from Call Report Schedule RC.	UBPR

Consolidated First Stages of Instrumental Variables Regressions

This table presents the combined results of the first stages of all the instrumental variables regressions. Column 1 presents the first stage for the IV regression presented in Table 3, column 4. Columns 2,3,4, and 5 presents the first stage results for Table 4, column 3,4,7, and 8. Columns 6 and 7 report the first stages for column 4 for Table 7 and Table 8, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Table III	**Table IV-3**	**Table IV-4**	**Table IV-7**	**Table IV-8**	**Table VII**	**Table VIII**
Instrumental Variable	0.9022***	0.8467***	0.8049***	0.9030***	0.9100***	0.9134***	0.9134***
	(0.00)	(0.12)	(0.14)	(0.12)	(0.13)	(0.11)	(0.14)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Dependent Vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,706	1,070	1,124	973	1,019	1,706	1,365
Kleibergen-Paap Wald F-stat	72	44	119	43	104	65	94

C Additional Tests and Figures

C.1 Bank-Year Effect of MDI Mergers

For the internal validity of all the results in the previous sections, the effects should be present at a firm level otherwise MDI-CB mergers treatment variable are not capturing the effect of credit supply decline due to banking presence. Figure C.1 and Figure C.2 documents the effect of MDI mergers and the lending supply at the bank-year level. As can be clearly inferred, both in level and percentage terms, the consolidated bank is lending significantly less to minorities following the loss of MDI status. Restricting my sample to only community banks further ensures that both treated and control banks are local in their geographical footprint and have similar asset sizes (recall that about 87% MDIs qualify as community banks) and observed differences in minority lending between the two groups are not driven by firm size. Formally, I estimate the following model:

$$log(y_{b,t}^{minority}) = \alpha + \beta_t \sum_{\tau} \mathbf{I}_{t=\tau} \cdot \mathbf{Treated}_b + \beta_2 X_{b,t-1} + \gamma_b + \theta_t + \varepsilon_{b,t}, \quad (12)$$

where $y_{b,t}^{minority}$ is the amount of the mortgages extended to the applicants of Asian, African-American, Native American and Hispanic communities for owner-occupied home purchases by a bank b in a year t. $\mathbf{Treated}_b$ is a bank-level indicator that takes on a value of 1 if an MDI merges with a non-MDI community bank (MDI-CB). $\mathbf{Treated}_b$ takes a value of 0 (Control banks) when a community MDI merges with another community MDI (MDI-MDI). $\mathbf{I}_{t=\tau}$ is a set of indicators that take a value of 1 when a year is t years relative to the year of bank-merger (t=0). $X_{b,t-1}$ is a set of lagged bank-level controls that include: natural log of total assets and total equity capital, short term non-core funding (% of Total

Assets), total real estate loans (% of Tier-1 Capital) and cost of all interest-bearing funds(%). γ_b and θ_t are bank and year fixed effects, respectively.

Figure C.1: Minority mortgage lending around MDI mergers

This figure plots the coefficients of the following model:

$$log(y_{b,t}^{minority}) = \alpha + \beta_t \sum_{\tau} \mathbf{I}_{t=\tau} \cdot \mathbf{Treated}_b + \beta_2 X_{b,t-1} + \gamma_b + \theta_t + \varepsilon_{b,t}, ,$$

Y-axis represents log of mortgage origination to minorities, $y_{b,t}^{minority}$, defined as amount of mortgage origination to applicants of Asian, African-American, Native American and Hispanic communities for all owner occupied home purchases by a bank b in a year t. X-axis represents the years relative to year of bank-merger denoted by the red vertical line. $\mathbf{Treated}_b$ bank is defined as an MDI that has merged with another non-MDI community bank. Control banks are MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated banks ($\mathbf{Treated}_b$) with with dummies for years relative to the year of bank-merger ($\mathbf{I}_{T=t}$). Lagged bank-year level controls include natural log of total assets and total equity capital, short term non core funding (% of Total Assets), total real estate loans (% of Tier-1 Capital) and cost of all interest-bearing funds(%). Standard errors are clustered at the bank-tract level. All continuous variables are winsorized at 99%

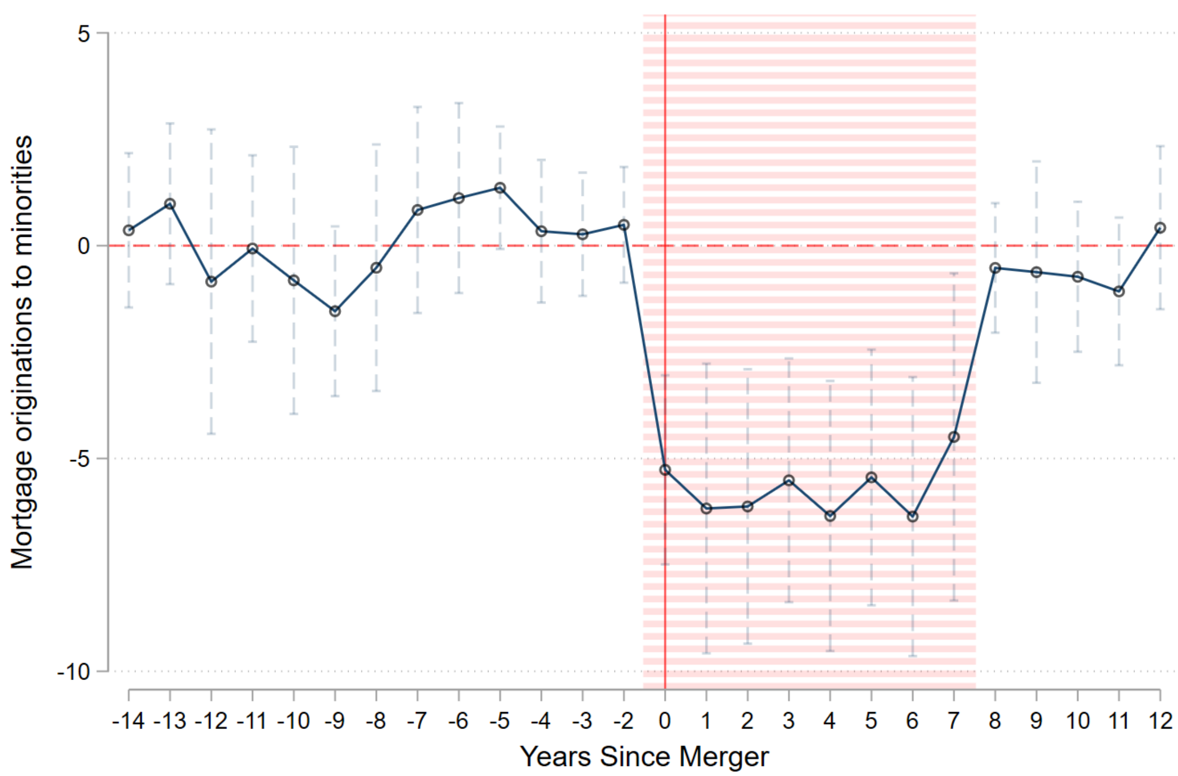
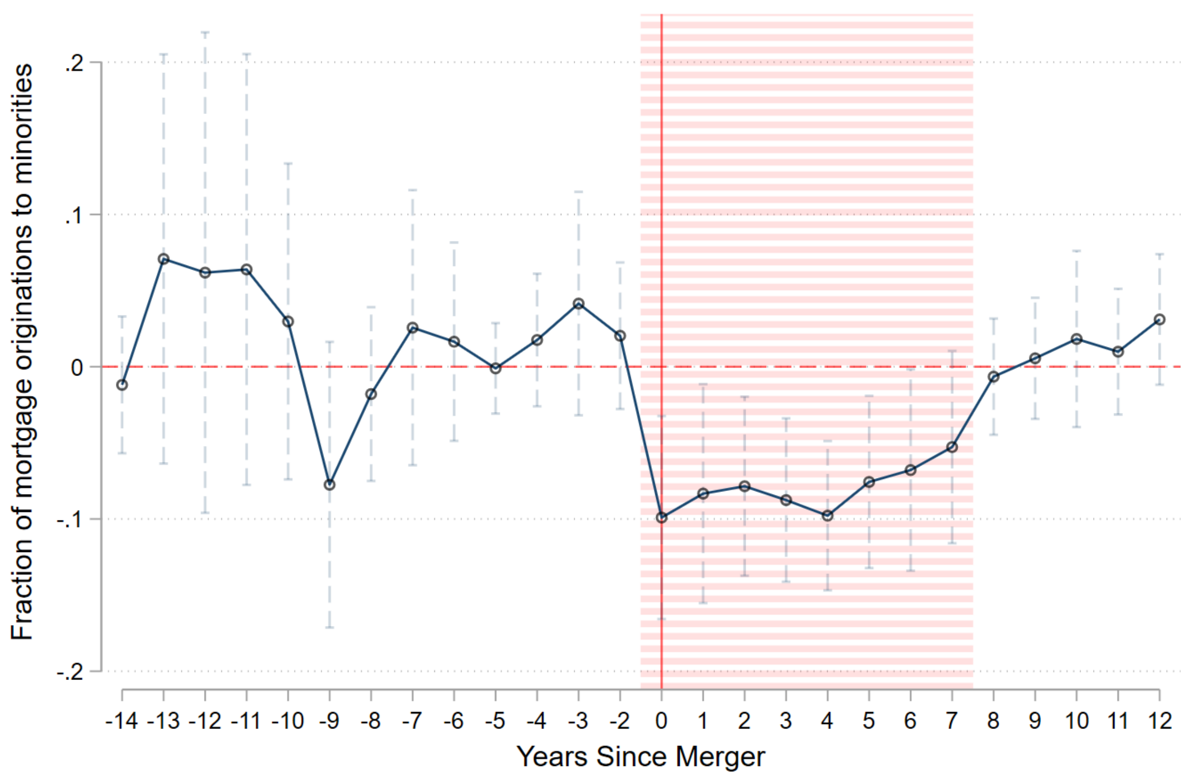


Figure C.2: Fraction of minority mortgage lending around MDI mergers

This figure plots the coefficients of the following model:

$$\mathcal{F}_{b,t}^{minority} = \alpha + \beta_t \sum_{i=-14}^{+12} \mathbf{I}_{T=t} \cdot \mathbf{Treated}_b + \beta_2 X_{b,t-1} + \gamma_b + \theta_t + \varepsilon_{b,t},$$

Y-axis represents mortgage origination amount to minorities as a fraction of bank's total real estate loans. X-axis represents the years relative to year of bank-merger denoted by the red vertical line. $\mathbf{Treated}_b$ bank is defined as an MDI that has merged with another non-MDI community bank. Control banks are MDIs that have merged with another MDI. Main explanatory variables are the interaction of treated banks ($\mathbf{Treated}_b$) with with dummies for years relative to the year of bank-merger ($\mathbf{I}_{T=t}$). Lagged bank-year level controls include natural log of total assets and total equity capital, short term non core funding (% of Total Assets), total real estate loans (% of Tier-1 Capital) and cost of all interest-bearing funds(%). Standard errors are clustered at the bank-tract level. All continuous variables are winsorized at 99%



C.2 Non mortgage lending

Does the presence of MDIs only matter for minority mortgages or does it percolate to other types of lending well? While it is true that MDIs are primarily real estate lenders, a significant portion of lending by them is also commercial lending backed by non-farm non-residential real estate. To the extent that MDIs report such CRE lending as small business loans via their CRA reporting, I should be able to get rough estimates of the effect of MDI presence on small business loans. I estimate the same specification as in equation *1*, using small business loans of less than $100,000 as the dependent variable to arrive at these rough estimates. The choice of principal amounts less than $100,000 makes sense because business loans by MDIs are likely to be to poor minority borrowers, given that it is the typical profile of their primary service area customer (refer to section A.4) and the fact that small business loans markets are still very local (Nguyen (2019)). Table C.III presents the results. Minority percentage and tract income have the usual impact of reducing the supply of credit, however, in column (4), the three-way interaction term loads positively and statistically significantly. However, the economic impact is modest and only prevalent in relatively richer tracts, where ceteris paribus, 100% increase in MDI share increase small business loans by about $40,000 against a sample average of $1.3 million. It is important to note two aspects on why any estimate of MDIs presence on small business lending should only be a rough estimate. One, only banks greater than $1 billion in asset size are required to report small business loans. Consequently, only 64 unique MDIs (40%) reported CRA loans on small business lending, while about 175 unique MDIs have reported HMDA loans during my sample period. Two, unlike HMDA, CRA data is not available across different borrower races rendering me unable to pin down the commercial lending done by MDIs to minorities, yet under the assumption that MDIs mainly provide loans to minority borrowers, these numbers represent rough estimates.

Table C.III: SBL originations in a census tract

Dependent variable is the logarithm of total Small Business Loan (SBL) amounts of less than $100,000 in principal valuein a census tract-year. Main explanatory variables are the interaction of minority fraction with median family income relative to MSA family income(MFI fraction) and MDI deposit share. All specifications control for lagged tract level controls including number of households, minority percentage, median family income relative to MSA family income(MFI fraction), Herfindahl Index and number of branches in a tract. Standard errors are in parentheses and are clustered at the tract level. All continuous variables are winsorized at 99%.

	Log SBL originations			
	(1)	(2)	(3)	(4)
zMinority %	-0.0335***		-0.0426***	-0.0332***
	(0.01)		(0.01)	(0.01)
zMFI Ratio	-0.0188***	-0.0223***		-0.0190***
	(0.00)	(0.00)		(0.00)
zMinority % × zMFI Ratio	-0.0077***			-0.0082***
	(0.00)			(0.00)
zMDI Market Share		0.0010	0.0004	-0.0016
		(0.00)	(0.00)	(0.00)
zMDI Market Share × zMFI Ratio		-0.0022*		-0.0046***
		(0.00)		(0.00)
zMDI Market Share × zMinority %			-0.0000	0.0008
			(0.00)	(0.00)
zMDI Market Share × zMinority % × zMFI Ratio				0.0018**
				(0.00)
Controls	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Observations	542,609	542,609	542,609	542,609
Adjusted R^2	0.8970	0.8970	0.8970	0.8970

* p<0.10, ** p<0.05, *** p<0.01

Figure C.3: Community bank definition FDIC

This figure taken from FDIC quarterly report on community banking mergers attests to the fact the in the 2007-2016 period, small community banks such as MDIs and other small community banks saw a merger boom among the same peer group Kowalik et al. (2015).

Summary of FDIC Research Definition of Community Banking Organizations

Designate community banks at the level of the banking organization. All charters under designated holding companies are considered community banking charters.

<u>Exclude:</u>

Any organization with:
- No loans or no core deposits
- Foreign Assets ≥ 10% of total assets
- More than 50% of assets in certain specialty banks, including:
  - credit card specialists
  - consumer nonbank banks[1]
  - industrial loan companies
  - trust companies
  - bankers' banks

[1] Consumer nonbank banks are financial institutions with limited charters that can make commercial loans or take deposits, but not both.

<u>Include:</u>

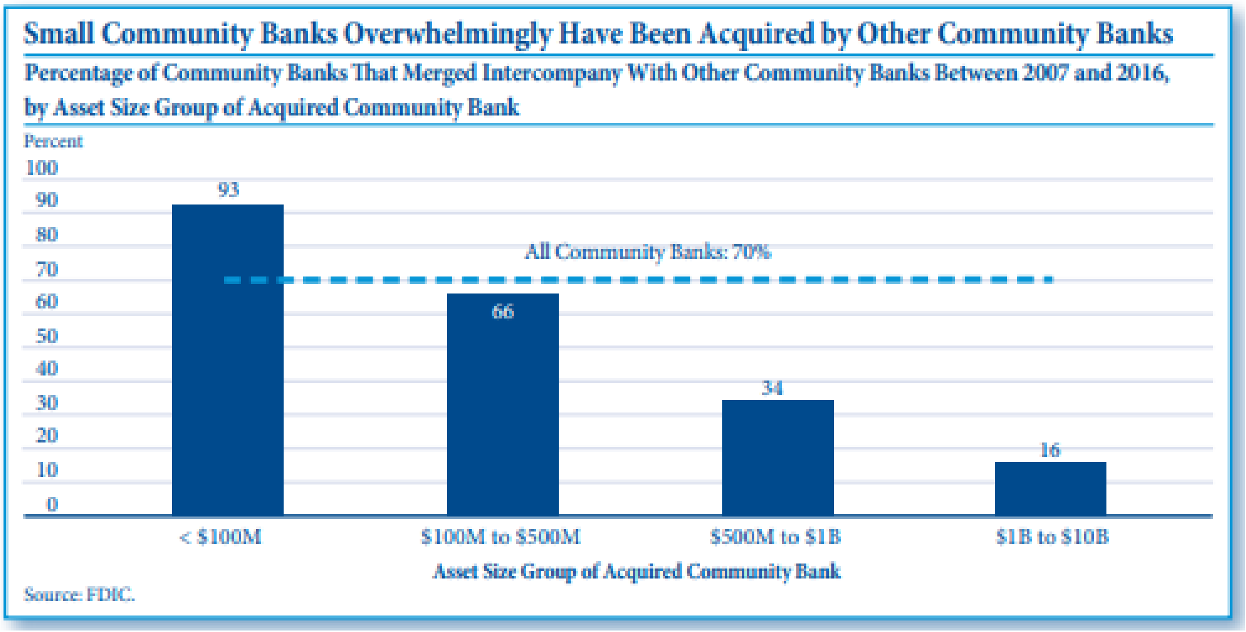
All remaining banking organizations with:
- Total assets < indexed size threshold[2]
- Total assets ≥ indexed size threshold, where:
  - Loan to assets > 33%
  - Core deposits to assets > 50%
  - More than 1 office but no more than the indexed maximum number of offices.[3]
  - Number of large MSAs with offices ≤ 2
  - Number of states with offices ≤ 3
  - No single office with deposits > indexed maximum branch deposit size.[4]

[2] Asset size threshold indexed to equal $250 million in 1985 and $1 billion in 2010.
[3] Maximum number of offices indexed to equal 40 in 1985 and 75 in 2010.
[4] Maximum branch deposit size indexed to equal $1.25 billion in 1985 and $5 billion in 2010.

Source: FDIC.

Figure C.4: Community bank mergers in wake of the financial crisis

This figure taken from FDIC quarterly report on community banking mergers attests to the fact the in the 2007-2016 period, small community banks such as MDIs and other small community banks saw a merger boom among the same peer group Kowalik et al. (2015).



D Geocoding

D.1 Geocoding SOD to a census tract level

The Statement of Deposits (SOD) database is a powerful database that allows a researcher to map a bank's market shares with bank lending and other banking databases. However as the data gathering processes have evolved, SOD has developed some inconsistencies. The minutest geographic precision with which the SOD data are available at the zip-code level. However, due to the paucity of banking and other economic data at zip-code level restricts data analyses usage of SOD to a county-level, as best. For smaller banks like MDI, the impact is hyper-local, and based on branch relationships. To be able to pinpoint the exact location, the XY coordinates or Latitude Longitude information must be consistently available. It is available only 2008 onward. Moreoever, the variable uninumbr, corresponding to unique branch location is not defined for most banks in years prior to 2011 and in some cases provides a many-to-one correspondence between banks and branch location Bord (2017). To perform my analysis at a census tract level I enhance the SOD data using the Lat/Long information, where available. Using the latitude and longitude information and shapefiles from census vintages 1990, 2000, and 2010 I perform a **spatial join** for locating the X-Y co-ordinate to be precisely within the census tract polygon. The centroid of every census tract polygon corresponds to the FIPS code of the census tract.

This process requires converting WGS84 geodetic datum census tract shape files to obtain a set of XY coordinates corresponding to the tract polygon and then reporting the tract FIPS code of the centroid, thus connecting an observation in SOD to FIPS code of the census tract. Using XY coordinates from SOD and shapefiles in ArcGIS software I locate the geography within the tract polynomial separating out the coordinate data from other data. For cases where latitude longitude information is not provided, I use the physical street address and convert the physical address to a latitude longtitude location and repeat the process of locating the given lat/long pair with a tract and reporting the FIPS associated with the centroid of the polygon. I am able to map all but 194,591 observations in the SOD to their FIPS for sample betweem 1996-2019, about 9 percent. Table D.IV reports the statistics of the geocoding procedure.

Table D.IV: Efficiency of the Geocoding Procedure

Unmatched Observations				
Year	Freq.	Percent	Cum.	% Unatched
1996	15,333	7.88	7.88	0.70%
1997	14,146	7.27	15.15	0.65%
1998	13,254	6.81	21.96	0.61%
1999	12,449	6.4	28.36	0.57%
2000	11,885	6.11	34.47	0.54%
2001	11,492	5.91	40.37	0.53%
2002	10,574	5.43	45.81	0.48%
2003	12,962	6.66	52.47	0.59%
2004	12,456	6.4	58.87	0.57%
2005	12,492	6.42	65.29	0.57%
2006	12,499	6.42	71.71	0.57%
2007	11,999	6.17	77.88	0.55%
2008	15,453	7.94	85.82	0.71%
2009	11,936	6.13	91.95	0.55%
2010	9,203	4.73	96.68	0.42%
2011	665	0.34	97.02	0.03%
2012	814	0.42	97.44	0.04%
2013	1,261	0.65	98.09	0.06%
2014	1,450	0.75	98.83	0.07%
2015	798	0.41	99.24	0.04%
2016	764	0.39	99.64	0.03%
2017	358	0.18	99.82	0.02%
2018	184	0.09	99.92	0.01%
2019	164	0.08	100	0.01%
Total				8.91%