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Do minority banks matter?☆

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ABSTRACT

This paper estimates the elasticity of minority credit supply to deposit shares of Minority Depository Institutions (MDIs). I use within-county tract-level variation in exposure to the Community Reinvestment Act and show that if a census tract loses MDI presence following a merger between an MDI bank and a community bank, its minority mortgage credit declines by 40%. These effects are driven by the loss of operationally efficient MDIs, and about half of the overall impact is attributable to the loss of mission alone. A 1% increase in county market shares of such tracts leads to roughly a 3% decrease in county-level minority homeownership.

1. Introduction

Ensuring equitable access to credit for minority groups is a long-standing policy objective. Over the past several decades, governments have implemented a series of regulatory interventions,[1] premised on the assumption that targeting low-income borrowers would *de facto* mitigate the frictions faced by minority households in credit markets. Yet, a growing body of evidence demonstrates that, despite these efforts, minority borrowers with equivalent credit risk continue to face higher interest rates, reduced service quality, and persistent obstacles in accessing capital.[2] This paper examines how a complementary credit delivery model—minority depository institutions (MDIs)[3]—may enhance the efficacy of existing policy frameworks in addressing these persistent disparities.

MDIs represent only 2% of the U.S. banking system, but they receive consistent policy attention for their role in serving historically underserved communities.[4] Still, their systemic impact on credit access remains empirically understudied. This paper helps fill that gap by quantifying the sensitivity of minority credit outcomes to the loss of local MDI presence. The central finding — on which the rest of the analysis builds — is that MDI absorptions, particularly by acquirers lacking a comparable community mission, lead to substantial declines in mortgage credit flows to minority borrowers (Fig. 1).

I estimate these effects using a difference-in-differences design, augmented by an instrumental variables strategy. The analysis compares treated tracts — those that lose their local MDI presence following a merger with a non-mission-driven community bank — with two different sets of control tracts. To identify the overall effect of MDI loss, I compare the treated tracts to those where the MDI landscape remains unchanged, with no mergers or ownership transitions. To isolate the marginal effect of losing an MDI, I compare the treated tracts to those affected by an MDI–MDI merger, where both sets of tracts experience a merger, but only the treated tracts lose their MDI. At baseline, I find that minority mortgage originations decline by about one-third (–0.37 log points) to one-half (–0.64 log points), on average, in treated tracts—the former capturing the marginal effect of losing mission continuity, and the latter reflecting the overall impact relative to an unchanged MDI environment.

However, these average effects conceal an important asymmetry: not all MDI losses are equally welfare reducing. Lending declines are concentrated in cases where the most operationally efficient or profitable MDIs are acquired. As shown in Fig. 2, minority mortgage originations fall by over 40% (–0.53 log points) when low-loss MDIs are

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[1] The most prominent laws being: the Community Reinvestment Act, Equal Credit Opportunity Act, and the Fair Housing Act.

[2] See Bartlett et al. (2021), Begley and Purnanandam (2021) and Fairlie et al. (2020).

[3] Defined under FIRREA §308 as banks that are minority-owned or governed and with a ***mission*** to serve minority communities. See Appendix A.

[4] Federal Reserve: Preserving and Promoting Minority Depository Institutions.

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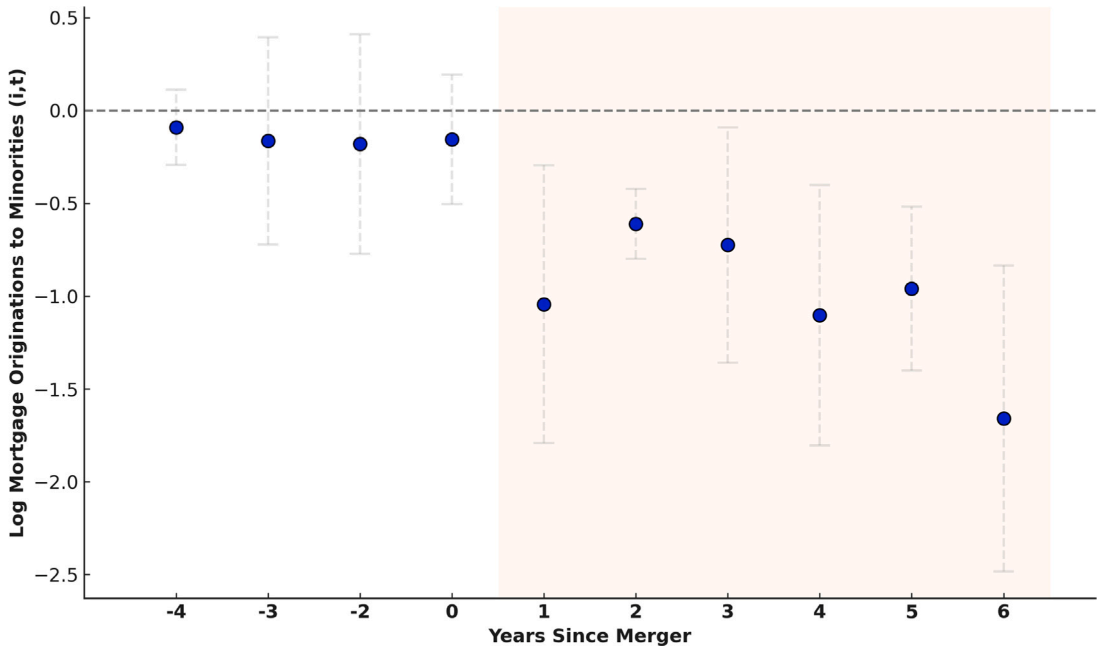


Fig. 1. Difference in Differences around MDI mergers.
This figure plots the coefficients of the following model:

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

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 have merged with another MDI. Main explanatory variables are the interaction of treated tracts ($\mathbf{Treated}_i$) 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%. The model also includes $\gamma_{c,t}$ fixed effects, denoting that the comparison is controlling for within county-year variation.

acquired, relative to both control groups. A similar pattern emerges for profitability: acquisitions of high-profit MDIs reduce minority lending by about 53% (–0.76 log points) relative to MDI–MDI controls and by roughly one-third (–0.37 log points) relative to MDIs with no ownership change. By contrast, there is no statistically significant change in lending when high-loss or low-profit MDIs are acquired—and point estimates in these cases even have a positive tilt.

These results suggest that the loss of minority credit access is mostly concentrated among takeovers of operationally efficient MDIs. When mission-driven lenders with strong performance metrics are absorbed by acquirers lacking a similar orientation, minority borrowers experience sharp declines in credit access. By contrast, takeovers of underperforming MDIs have little measurable impact and may even reflect efficiency gains. Together, these findings imply that sustaining minority lending in the wake of institutional change requires both mission continuity and institutional capacity—one without the other may be insufficient.

Beyond average effects, I also find that the consequences of MDI loss vary by MDI identity (see Fig. 6) and control group composition (Fig. 3). I explore this heterogeneity through subsample analyses limited to mergers involving only Asian, Hispanic, or African/Native American MDIs. Estimates show that losing an Asian American MDI leads to a modest but statistically significant decline in minority mortgage originations: about 20% (−0.26 log points) in the MDI-MDI control group (relative to a baseline of –0.37), and about 40% (−0.50 log points) in the MDI -No Change group (relative to baseline of −0.64 log points). In contrast, the loss of Hispanic MDI produces the steepest decline in the MDI-MDI comparison, about 60% (−0.75 log points), which far exceeds the baseline, but a smaller drop of about one third (−0.32 log points) relative to the MDI-no change group.

This pattern reflects two distinct but plausible mechanisms. The sharper decline following Hispanic MDI mergers — relative to MDI–MDI controls — may reflect greater borrower vulnerability. Hispanic households often rely on culturally embedded and flexible lending practices offered by mission-driven MDIs, making them more exposed when non-mission-oriented acquirers replace such institutions. In contrast, Asian households tend to have higher incomes and likely benefit from broader access to mainstream credit sources, which may mitigate the impact of MDI loss. I do not directly observe borrower credit characteristics in my data. As a result, these mechanisms are inferential—plausible given the observed patterns, but ultimately speculative due to data limitations. Future research using borrower-level microdata could more precisely isolate the underlying channels.

To unpack the mechanisms behind the observed credit effects, I construct a GIS-based panel tracking the ownership and operational status of every U.S. bank branch over two decades. This allows me to observe the post-merger fate of the affected MDI branch in each treated tract,[5] specifically whether it closes or remains open under new ownership. This distinction enables me to separate cases involving both mission and physical loss from those involving ownership change alone, and to isolate effects of merger-driven closures from routine reductions in branch networks.

As expected, the sharpest lending declines follow the combined loss of mission and physical presence (Fig. 4-Panel A). Comparisons across scenarios help isolate the contribution of each channel. Compared to tracts with no change in mission (either due to branches remaining open after MDI-MDI mergers or because the MDI landscape remained

[5] Summary statistics show that the mean and 75th percentile number of MDI branches in treated tracts is one.

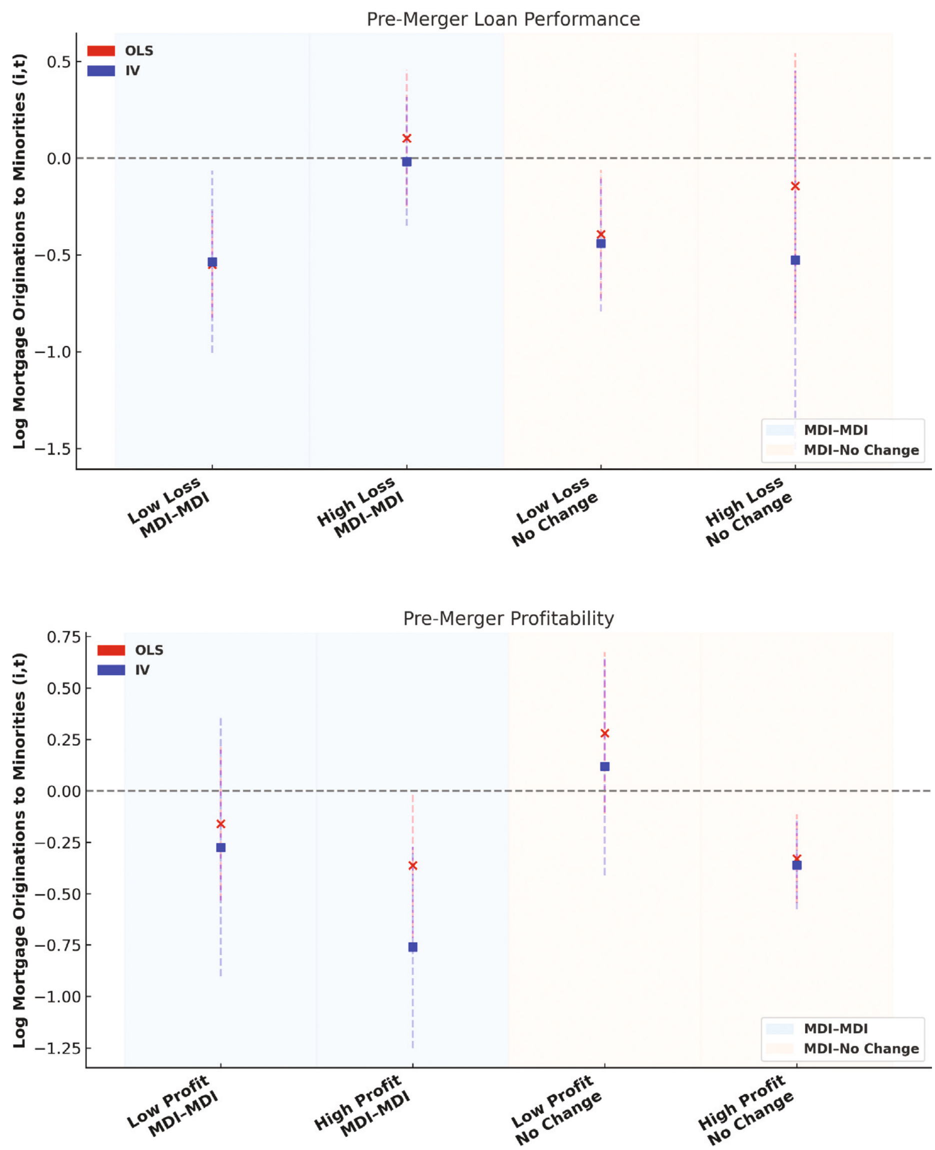


Fig. 2. Effect of Pre-Merger MDI Performance.
This figure presents OLS and IV estimates of the effect of MDI–Community bank mergers on mortgage originations to minority borrowers. The estimates correspond to the model specified in Eq. (2) and are disaggregated by the pre-merger performance of the acquired MDI. Performance is measured using quartiles of net loan losses subfigure (a) and net operating income subfigure (b). Low and High correspond to the lowest and highest quartiles, respectively. Treated tracts are those that lose local MDI presence following a merger with a non-MDI community bank. Estimates over the blue background use MDI–MDI mergers as the control group; those over the beige background use MDIs with no ownership change. All regressions include tract and county-year fixed effects and control for a full set of lagged tract-level covariates. All continuous variables are winsorized at the 99th percentile and standard errors are clustered at the county level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

unchanged), post-merger closures result in an average lending decline of about 60% across the two control groups. In comparison, the effect attenuates to approximately 35%, on average across the two control groups, when the post-merger branches remain open. These patterns suggest that roughly half to two-thirds of the lending decline following MDI-CB mergers can be attributed to mission loss alone. The framework also allows me to observe post-merger scenarios relative to non-merger-related branch closures, where an attenuated negative effect is observed.

To assess borrower consequences, I examine mortgage denial rates and whether effects vary with pre-merger branch size. In general, the denial effects are positive but statistically insignificant, suggesting that there is no significant increase in denials across the full set of mergers (Fig. 4-Panel B). The results are more indicative of the borrower disengagement mechanism than of increased credit rationing after the acquisition of MDI.

I also examine whether treatment effects vary with the pre-merger size of the affected branch by estimating the main specification separately for branches above and below the county median in deposit share. As shown in Fig. 4-Panel C, the negative impact is concentrated in areas served by smaller branches, while no significant effect is observed for larger ones. This suggests that the consequences of MDI loss are most acute where the institutional presence was already limited—likely because smaller branches are more vulnerable to closure or operational disruption, and borrowers more dependent on trust-based, community-embedded lending relationships.

Finally, I aggregate local tract-level results to household outcomes at the county level using two large, nationally representative surveys: the American Community Survey (ACS) and the CPS March supplement. I use the ACS to measure county-level minority homeownership rates and the CPS to estimate the reduction in the probability of minority renters transitioning into homeownership. Across both datasets,

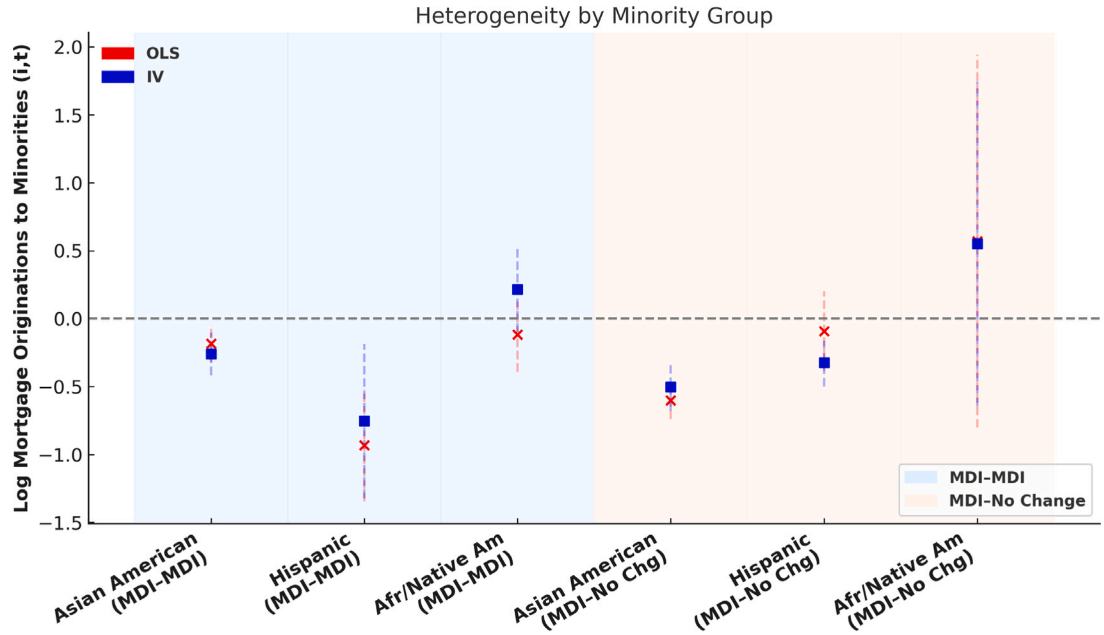


Fig. 3. Effects by MDI Heterogeneity.
This figure presents OLS and IV estimates of the effect of MDI–Community bank mergers on mortgage originations to minority borrowers. The estimates correspond to the model specified in Eq. (2), and are disaggregated by minority group and type of control group. Estimates over the blue background use MDI–MDI mergers as the control group; those over the beige background use MDIs with no ownership change. All regressions include tract and county-year fixed effects and control for a full set of lagged tract-level covariates. All continuous variables are winsorized at the 99th percentile and standard errors are clustered at the county level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

I find that a one percentage point increase in the deposit share of treated tracts is associated with about a 3% adverse impact on minority homeownership. I further stratify the analysis by geographic context, focusing on large metropolitan areas, central cities, and suburbs—and find that the effects are smaller in suburban areas relative to principal metro cities, where housing markets tend to be more competitive.

A central concern in interpreting the above findings as causal is that MDI–community bank mergers may reflect endogenous responses to local economic conditions. For instance, weakening credit demand or declining MDI profitability could precipitate a merger, rather than mergers causing a decline in credit. Given that pre-existing economic conditions for MDI can drive community bank mergers, I employ an instrumental variables strategy to better isolate the causal effect of the loss of MDI on minority credit access. This approach ensures that my estimates account for endogeneity and provide a more accurate estimate of the impact.

I construct an instrument based on a tract's *ex ante* exposure to Community Reinvestment Act (CRA) evaluations, which introduces plausibly exogenous variation in the likelihood of MDI–CB mergers. Specifically, I define a time-varying, tract-level CRA intensity measure as the share of local deposits held by banks undergoing or imminently scheduled to undergo CRA performance evaluations, scaled by the tract's relative income. This construction reflects three regulatory facts: CRA assessments are geographically defined, disproportionately target low-income tracts, and create compliance pressure in proportion to local deposit exposure.[6] The average over two years accounts for both the anticipatory behavior of banks (Agarwal et al., 2012) and the multi-quarter duration of CRA exams (Reid et al., 2013), which often span calendar years.

The inclusion restriction requires that CRA intensity predicts the likelihood of an MDI–CB merger. There are two explanations as to why this may be the case. First inclusion restriction is empirically testable, the instrument does predict the instances of MDI-CB mergers with very strong first test t-stats. Second, although CRA exams evaluate multi-year past performance — primarily under the lending test — banks often rely on non-lending CRA activities for credit, such as investments in or partnerships with MDIs as outlined in FDIC guidance. Banks often act preemptively in anticipation of upcoming evaluations. Objective as the CRA evaluation may be, banks often expect subjective activities to qualify for CRA credit.[7] As a result, acquiring an MDI can serve as a compliance-enhancing strategy, particularly for banks facing heightened regulatory scrutiny or seeking approval for expansion.

Additional evidence from Brevoort (2022) shows that banks respond to CRA incentives by purchasing existing loans rather than originating new ones, allowing them to earn CRA credit through activities that generate immediate compliance benefits without increasing future credit supply to LMI areas. In a similar spirit, it is plausible that some banks pursue strategic investments in MDIs to earn CRA credit at the time of acquisition via qualified investment activity, even if they do not intend to sustain mission-driven lending thereafter. These findings help show that CRA credit can be *symbolic or short-term in nature*, reinforcing the relevance of the instrument as a predictor of merger activity rather than sustained credit expansion. This question remains policy-relevant today, as MDI acquisitions continue to occur—including several in 2023 that led to a further decline in the number of active MDIs[8]

Finally, the exclusion restriction is also plausible. CRA exam schedules are regulator-driven and unrelated to specific tract-level shocks. Variation in tract CRA intensity arises from exogenous orthogonal institutional factors—preset exam calendars, regulatory assignments, and changes in bank market shares, and exogenous reclassifications of relative tract income due to census and ACS updates. Moreover, if CRA

[6] CRA evaluations weight performance expectations by a bank's market footprint CRA exam manual.

[7] For the same reason banks expect community development activities to qualify for CRA credit.

[8] In 2023, three Asian American and one Hispanic American MDIs were acquired by non-MDI institutions and subsequently removed from the official MDI list. See: FDIC (2023), Minority Depository Institutions Program: 2023 Summary Profile.

pressure directly increased minority lending, I should observe a positive reduced-form effect as sanity check. Instead, I find the opposite: lending declines with higher CRA intensity, consistent with the exclusion restriction. The empirical section provides detailed supporting evidence for the instrument's validity.

These findings carry important regulatory implications. While Section 308 of FIRREA expresses a policy commitment to preserve the minority character of MDIs during mergers,[9] the evidence suggests that a closer look at MDI mergers may be warranted — especially in cases involving high-performing institutions — so that the intended goals of preservation are more effectively realized.

If even a portion — say, 20% — of non-assisted MDI acquisitions are motivated in part by CRA-related incentives, the resulting decline in minority credit access and homeownership in remote pockets of the US (Fig. 5) constitutes a regulatory externality. Given the $250 billion size of the first-time minority home-purchase market in 2017, a 37% reduction implies a back-of-the-envelope lower-bound impact of approximately $92 billion that can be attributed to MDIs.

My paper relates to, and contributes to a few different strands of the literature. First, it relates to the vast literature on the role of banks in overcoming capital market frictions. Petersen and Rajan (1994) provide 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) find that inter-bank competition tends to increase relationship lending but at a lower marginal benefit to the borrower. Fisman et al. (2017) find that shared cultural background increases 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, this paper contributes to the literature that evaluates financial inclusion mechanisms. Burgess and Pande (2005) find that rural banks are important for alleviating poverty. Banerjee et al. (2015) re-examine the role of micro-credit in fostering local development and find mixed evidence. Gilje et al. (2016) point to the continued importance of branch networks in financial integration, Nguyen (2019) confirms this using branch closures induced by large bank mergers. This paper contributes to this literature by quantifying the impact of post merger fate of MDI branches on small geography's minority homeownership.

Third, this paper contributes to the growing literature on financial intermediation under the Community Reinvestment Act. Lee and Bostic (2020) find that banks approve loans more frequently in those neighborhoods that are most rapidly improving, and that this effect is stronger if the neighborhoods are CRA-eligible. Agarwal et al. (2012) find that lending spikes just before CRA evaluation, suggesting compliance is often anticipatory. Brevoort (2022) highlights how banks can fulfill CRA obligations through strategic loan purchases rather than expanded originations. My paper extends this literature by showing that CRA compliance may adversely impact mission-driven intermediaries, which has real consequences for minority credit access.

2. Data

The empirical analysis in this paper uses data from multiple sources. This section provides a brief overview of various data sources. Details of the institutional background of MDIs are available in Appendix A, and a detailed list of all the main variables used along with their definitions and respective sources is available in Appendix B.

Following the existing 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 (UBPR) provided by the Federal Financial Institutions Examination Council (FFIEC). Data on all active and newly charted MDIs are available through the Federal Deposit Insurance Corporation (FDIC). The FDIC maintains a list.[10] 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 the FDIC's Reports of Changes to Financial Institutions & Office Structure database[11] 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[12] as well as data on community banks[13] available via the FDIC's community banking initiative. Using these databases, I can identify MDI mergers, MDI failures, and the type of acquisition bank (MDI Vs. Community Bank) and construct an event timeline before and after MDI mergers.

The smallest geographical level at which credit data are available, along with the race, geography, and time dimensions (from the Home Mortgage Disclosure Act (HMDA) database), is the census tract. Census tracts are homogeneous geographical areas demarcated for census purposes to define neighborhoods having 4000 to 8000 residents. Area-wise, their sizes are adjusted for population density (Fig. 5), with the average area being 1.5 square miles. The ACS 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 Summary of Deposits,[14] (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. Provides branch-level deposits, branch addresses, including ZIP codes, and, from 2008 onward, the bank branches' latitude and longitude. Using the ArcGIS software, I perform 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 small 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), and 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.

Credit supply information is available through the Federal Financial Institutions Examination Council (FFIEC) Home Mortgage Disclosure Act (HMDA) and Community Reinvestment Act (CRA) databases.[15] The HMDA database provides information on home mortgages extended by

[9] Federal Reserve Board (2016), Section 308 of FIRREA Report.

[10] https://www.fdic.gov/regulations/resources/minority/mdi.html.

[11] https://www5.fdic.gov/roc/Default.aspx.

[12] https://www.fdic.gov/Bank/individual/failed/banklist.html.

[13] https://www.fdic.gov/regulations/resources/cbi/data.html.

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

[15] https://www.ffiec.gov/.

a bank at census tract-year-race levels, while the CRA database provides similar information on small business loans at a tract-year level. Using multiple years of the American Community Surveys (ACS) and the decennial census of 1990, 2000, and 2010, I obtain rich demographic information on census tracts for a period ranging from 1996–2019. I also ensure that only mortgage loans to the represented minority are considered. For example, for an Asian-American MDI, the loans given to Asian-American borrowers will be considered.

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

3. Summary statistics

3.1. MDI summary statistics

The sample period for this analysis runs from 2001 through 2018. 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% versus 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 net operating profits after tax (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, Panels C-I and 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 Federal Housing Authority and Veterans Affairs mortgages.

At the 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 2% 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 area. Previous research (Toussaint-Comeau and Newberger, 2017; 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.

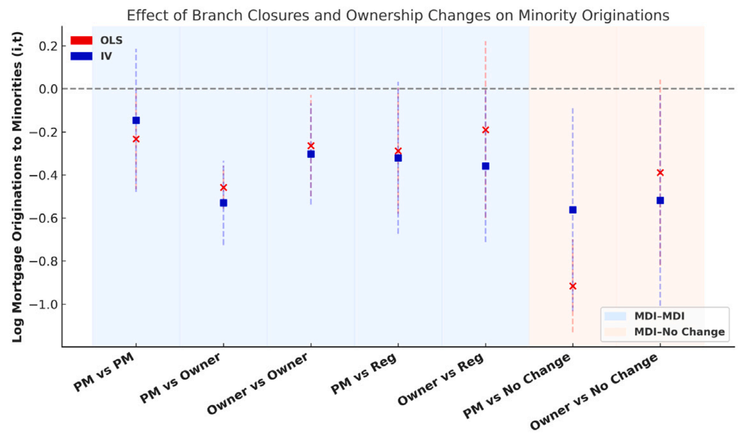
3.2. Merger sample

Table 1, Panel C-III shows the characteristics in my sample are similar along banking networks and demographics. Comparing treated tracts to across both types of control tracts we find that the tracts have the similar number of branches of traditional banks and MDIs, similar numbers of households, and income levels. Both the treated and control tracts are at 90%–95% of Metropolitan Statistical Area (MSA) income level and have 3–4 total branches and one MDI branch on average. However, some significant differences remain in that control tracts on average have a slightly higher minority population percentage, as they should, as both sets of controls represent pure MDI markets while the treated tracts present mixed markets (MDI-CB). Moreover, the distribution of minority mortgage credit exhibits a fatter right tail for the treated tracts. To address this, I use a log scale for my dependent variables in the empirical analysis and conduct a difference-in-differences analysis augmented by an instrument variable (IV) approach. This allows me to control for time-varying covariates and also establish the pre- and post-trends in mortgage origination, which I report graphically. The next section details the main results and empirical approach.

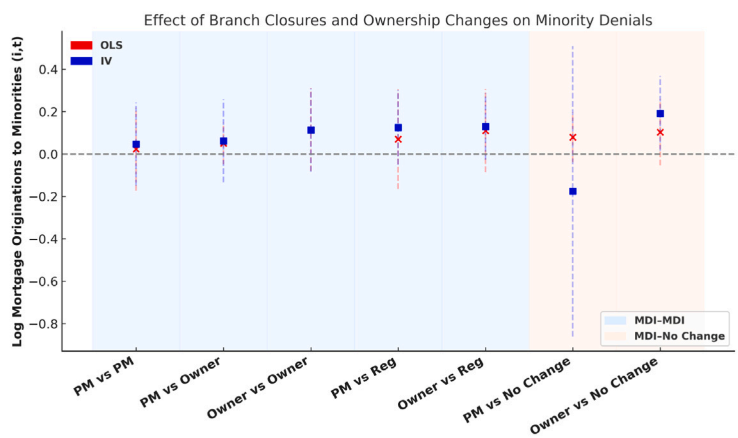
4. Identification and empirical framework

4.1. Does MDI presence lead to higher minority lending?

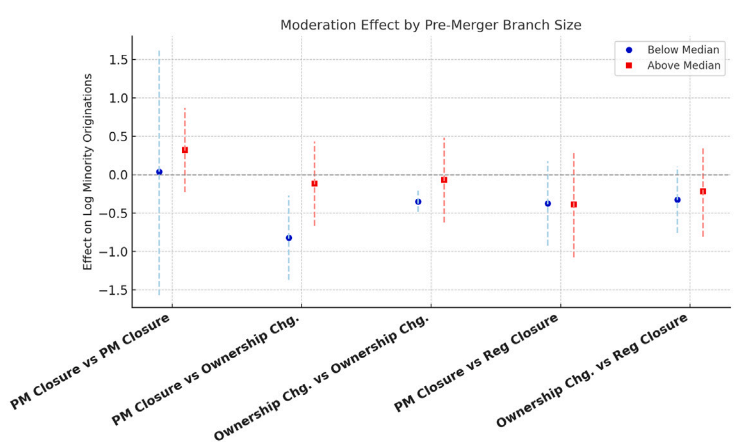
I begin by assessing whether MDI presence in local banking markets is associated with higher minority credit supply. Minority homeownership outcomes are closely linked to the tract's racial and economic composition, which influence credit demand through household-level primitives such as income, wealth, marital status, and family structure (Haurin et al., 2007). To isolate the marginal contribution of



Panel A: Effect on Minority Loan Originations



Panel B: Effect on Minority Loan Denials



Panel C: Effect Conditional on Branch Size

Fig. 4. Effect of branch closures and ownership changes.

MDIs and establish correlation, I estimate the following model using a saturated interaction specification:

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

where, for a census tract i in year t, $z\mathcal{S}_{i,t}$ is the MDI tract deposit share, $z\mathcal{R}_{i,t}$ is the tract to MSA family income ratio, $z\mathcal{M}_{i,t}$ is the percentage of minorities in a tract, and γ_i and $\theta_{c,t}$ are tract and county-year fixed effects, respectively, $(i \cdot t)$ controls for linear time trends. The lagged control vector $X_{i,t-1}$ includes: number of households (in '000s), minority share, tract-MSA income ratio, log tract deposits, Herfindahl

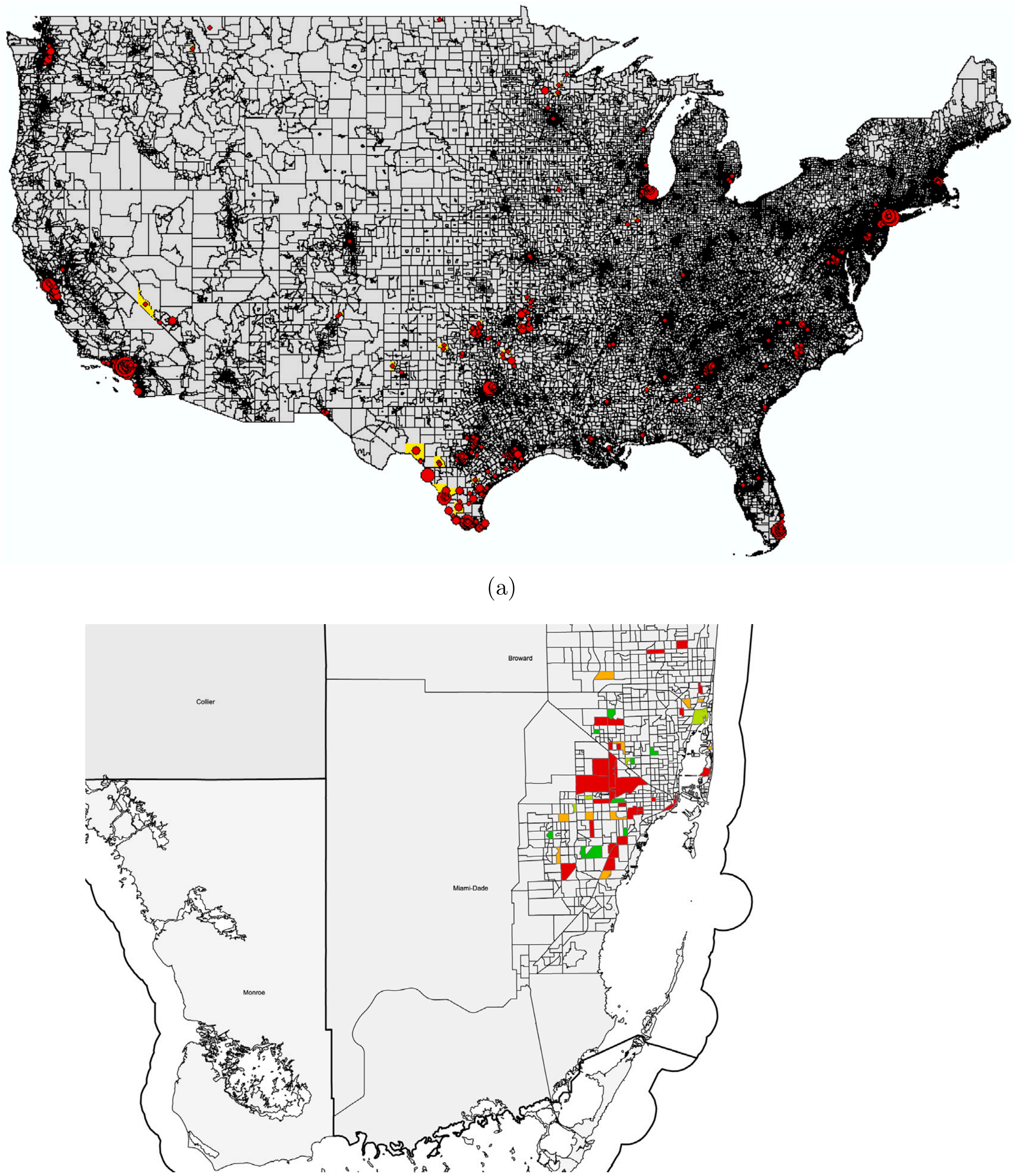


Fig. 5. Geographical presence of MDIs in US census tracts.
This figure presents the geographical location of MDIs in census tracts of contiguous United States (a) and in the Miami metropolitan area for reference in (b). Yellow colored tracts represent up to 25% deposit share, red tracts between 25% and 50% while blue tracts represent between 75% to 100% deposit share.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Author's calculation, ArcGIS, Summary of Deposits

index, and branch count is the standard set of vectors that I will use in the rest of the analysis.

The coefficient β_7 captures the triple interaction effect and is the parameter of interest. Column (5) of Table 2 presents the estimates. I find a positive and statistically significant β_7, suggesting that in relatively poor, minority-heavy tracts, the presence of MDIs boosts minority credit supply.

Fig. 8 provides a graphical illustration of the marginal effects for varying combinations of tract income and racial composition. Except in rare high-minority, high-income tracts (less than 0.5% of the sample), MDI presence increases minority lending. The increase ranges between 5% and 40% as MDI share moves from 0% to 100%.

These findings suggest a robust correlation but are not causal. MDI market share may still be endogenously determined in response to local economic conditions. I address this concern through a difference-in-differences design supplemented with an instrumental variables (IV) strategy exploiting quasi-random variation in CRA regulatory pressure.

4.2. Main results

4.2.1. Difference-in-differences estimation

I use an MDI merger-event as a source of change in MDI market share in a locality, the endogenous co-variate in Eq. (1). Prior literature has extensively used merger induced changes in market concentration to study various real effects such as crime (Garmaise and Moskowitz,

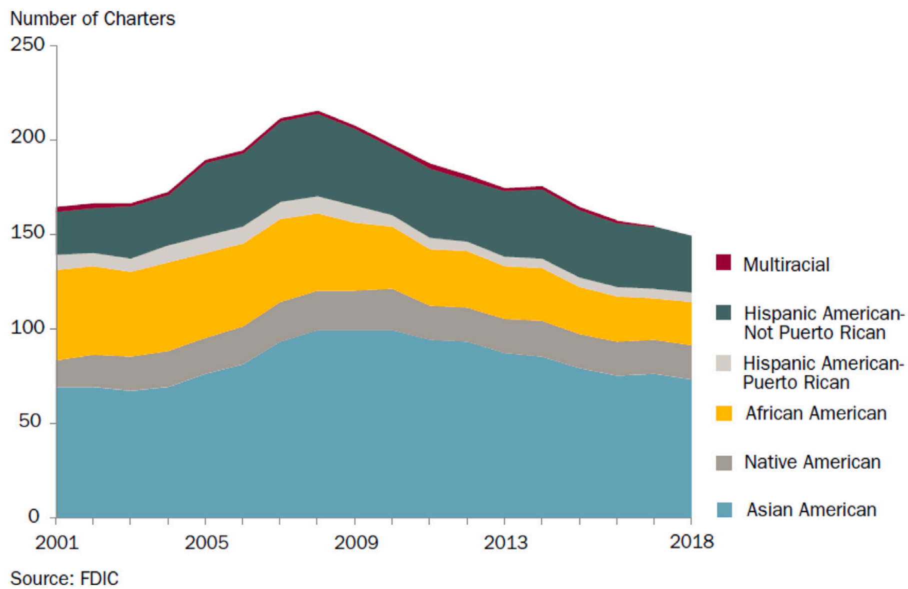


Fig. 6. Number of MDI charters by type. This figure presents the number of MDI charters by MDI minority type from 2001 through 2018. *Source:* FDIC report. https://www.fdic.gov/regulations/resources/minority/2019-mdi-study/full.pdf

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, in a generalized difference-in-differences framework as follows:

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

A tract i is assigned to the *treatment* group if the only MDI operating in that tract is acquired by a non-MDI community bank (an MDI–Community Bank merger), resulting in the loss of local MDI presence. $X_{i,t-1}$ denotes a vector of lagged tract-level controls described in the previous section. The indicator $\mathbf{Post}_t$ equals one for post-merger years. To ensure that estimated effects are not confounded by variation in institutional size, the analysis restricts the sample to mergers involving only community banks — whether MDI or non-MDI — based on the FDIC's official definition.[16] Provided the identifying assumption of parallel trends holds and treatment is as-good-as-randomly assigned, the coefficient of interest, β_1, yields an unbiased estimate of the impact of losing MDI presence on a tract's minority credit supply.

4.2.2. *Choice of control groups*

To estimate the coefficient of interest in Eq. (2), I use two distinct sets of control groups. For the overall effect of MDI loss, I use a control group consisting of tracts where the local MDI landscape remained unchanged. This setup captures the total effect of institutional change, combining both the removal of mission orientation and broader structural disruption. Because no actual merger occurs in these control tracts, I assign synthetic merger years using multivariate Mahalanobis distance matching.[17] Synthetic timing provides a consistent event-time structure with assigned pre- and post-periods for the control group, which is essential for implementing a difference-in-differences strategy and allows for the use of event study frameworks. However, it is important to recognize that synthetic timing serves as a proxy rather than a realized institutional event, which may introduce some estimation noise.

For the marginal effect of losing mission orientation, I compare treated tracts to those affected by MDI–MDI mergers. In this case, both groups experience a merger, but only the treated group loses mission continuity. Since the MDI–MDI control group has also observed a merger event, a natural event-time structure is already available in this group, allowing for clean identification without additional alignment.

These two control strategies help distinguish between the specific harm of losing a mission-driven institution and the broader consequences of institutional change. This distinction is not only empirical but also carries meaningful policy implications. By separately identifying the marginal effect of mission loss and the total effect of institutional turnover, I can assess whether the adverse outcomes stem from organizational disruption alone or from the removal of community-focused lending models. This matters for regulators and policymakers who must evaluate the risks and benefits of merger approvals, particularly when mission-driven institutions are involved.

I also plot the coefficients of a more general model as given below in Fig. 1 to test the parallel trends assumption.

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

Plotting the year dummy interactions with the treatment indicator provides a visual test of the parallel trends assumption. Fig. 1 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 six years after the MDI acquisition.

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 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 IV 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.

[16] See Figure C.4 for details.

[17] The matching procedure is based on lagged household count, minority share, MFI ratio, log of deposits, Herfindahl–Hirschman Index (HHI), lagged mortgage originations to minorities, and branch count. All matches are exact within county, and the first nearest neighbor is assigned the merger year of its treated counterpart.

4.2.3. Instrumental variable estimation

To address endogeneity in estimating the impact of MDI–Community Bank (CB) mergers, I construct an instrumental variable derived from regulatory compliance activity under the Community Reinvestment Act (CRA) of 1977. Banks are periodically evaluated for CRA compliance, and poor ratings can hinder growth through restrictions on branching and acquisitions. These evaluations emphasize whether banks sufficiently serve low- and moderate-income (LMI) tracts, creating incentives for banks to improve their CRA profile in advance of scheduled reviews. Specifically, I use the mean CRA intensity $\overline{C}_{i,t}$ of a tract i in years t and $t+1$ as an instrument to predict MDI–non-MDI mergers, where the annual CRA intensity $C_{i,t}$ is calculated as:

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

where for a bank b, census tract i in year t, $\mathcal{S}_{b,i,t}$ is the share of tract deposits held by bank b, $\mathbf{Exam}_{b,t}$ is an indicator for whether bank b is under CRA evaluation, and $\mathcal{R}_{i,t}$ is the tract MFI ratio. Richer tracts lower CRA intensity. The two-year average $\overline{C}_{i,t}$ captures both immediate and anticipated CRA pressure. I construct the instrument by merging CRA exam databases with geo-coded SODs using fuzzy string matching.[18]

I instrument the treatment variable in Eq. (2) with the mean CRA intensity to generate plausible exogenous variation in MDI–CB mergers and interpret the difference-in-differences results of the previous section causally. Following Windmeijer and Santos Silva (1997) and Wooldridge (2010) for IV estimators in the case of endogenous binary regressors, I first estimate the following linear probability model:

$$(\text{Treated} = 1 \mid \overline{C}, Controls) = \alpha + \gamma_{c,t} + \beta_1 \overline{C}_{i,t} + \beta_2 \mathbf{X}_{i,t-1} + \epsilon_{i,t}, \tag{5}$$

where $\overline{C}_{i,t}$ is the mean CRA intensity as defined above, and $\mathbf{X}_{i,t-1}$ is the same vector of lagged tract-level controls described earlier.

$\overline{C}_{i,t}$ loads statistically significantly (p-value < 0.01; $\beta = 21.07$). Next, to avoid the "forbidden" IV regression (where the predicted values from the first stage are directly substituted in place of the endogenous binary regressor), 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 Eqs. (2) and (3) under the 2SLS IV framework.

4.2.4. Assessing instrument validity: Inclusion and exclusion restrictions

A valid instrumental variables strategy hinges on two central assumptions: the instrument must meaningfully predict treatment assignment (the inclusion restriction), and it must influence the outcome variable only through its effect on treatment (the exclusion restriction). In this context, tract-level CRA intensity must both forecast the likelihood of an MDI–Community Bank merger and remain orthogonal to other unobserved determinants of minority lending.

The CRA intensity instrument is constructed to approximate localized regulatory pressure by leveraging institutional features of CRA enforcement. CRA evaluations are administered at the bank level, but they are geographically tied to where deposits are held and place greater scrutiny on low- to moderate-income (LMI) tracts. A tract's CRA intensity rises when a large share of local deposits is held by banks facing imminent evaluations—especially in poorer tracts, where regulatory weight is amplified.

In the extreme case, consider a tract where every bank is about to be evaluated and the tract is among the poorest in its MSA. Each bank is aware that its activity in this location will be closely scrutinized, creating strong forward-looking incentives to enhance its Community Reinvestment Act (CRA) performance. Banks may, in response, pursue non-lending but CRA-eligible strategies, such as equity investments, partnerships with MDIs, which explicitly qualify under the investment test.[19] A similar dynamic is observed in the Low Income Housig Credit (LIHTC) market, where banks earn CRA credit through community development investments. In fact, credit pricing varies with the CRA "hotness" in an area.[20] The spirit of the instrument used in this paper is similar: it captures fluctuations in area-level regulatory salience that may shape strategic responses by banks.

Institutions may act strategically to improve their compliance profile ahead of CRA evaluations. Agarwal et al. (2012) shows that banks increase lending to CRA-eligible neighborhoods in the few quarters preceding an exam.[21] Relatedly, CRA evaluations may also create incentives for banks to pursue symbolic or optical strategies to improve their compliance profile without meaningfully expanding credit access. Brevoort (2022) documents one such behavior, showing that because origination and loan purchases carry equal weight in CRA tests, banks inflate their CRA-qualified loan shares through purchases that have little impact on actual LMI credit originations, often by purchasing GSE-eligible loans. In this context, an MDI acquisition may serve as a similar compliance-oriented community development investment — and may even benefit the acquiring bank by bringing an entire CRA-eligible loan book under its portfolio — with no binding commitment to preserve the acquired institution's mission-based lending. Thus, the observed post-merger decline in minority lending does not undermine the instrument's validity but rather reinforces the mechanism linking CRA pressure to MDI–CB mergers.

Patterns in the data reinforce this interpretation. As shown in Fig. 9(a), non-MDI acquirers of MDIs complete more than 85 additional acquisitions in the five years following their MDI takeover, with over 80% of this activity occurring in the first year. Such forward-looking acquisition behavior suggests that banks anticipating future M&A activity may view MDI takeovers as a strategic move to bolster CRA credentials—especially since satisfactory CRA ratings are required for future merger approval. To capture the regulatory pressure faced by acquirers, I construct a bank-level CRA intensity measure:

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

where $\overline{C}_{i,t}$ is the two-year average CRA intensity in tract i and $\mathfrak{i}_{b,i,t}$ is the share of bank b's deposits held in tract i. As seen in Fig. 9(b), CRA pressure rises sharply in the three years leading up to an MDI–CB merger but remains flat for other types of acquirers. This temporal ordering strengthens the inclusion restriction by showing that CRA intensity precedes, rather than follows, MDI–CB mergers.

Empirically, the inclusion restriction is also strongly supported. In the first-stage regression, CRA intensity enters with a large and statistically significant coefficient, and the Sanderson–Windmeijer F-statistic exceeds conventional thresholds for weak instruments, as reported in all the tables. Full first-stage results are provided in the Appendix.

These acquisitions are not hypothetical. As shown in Fig. 7, of the 80 non-assisted MDI mergers in the data, about half involve non-MDI acquirers. This pattern persists through 2023 where three MDI acquisition, affirming that MDI–CB mergers are both real and ongoing. The empirical relationship between CRA pressure and MDI acquisition is consistent with a story of regulatory arbitrage: when CRA compliance

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

[19] 12 CFR §25.21 and related interagency Q&As confirm that such activities are CRA-eligible.

[20] See Novogradac, "A Look at LIHTC: Past Pricing Trends, Current Market and Future Concerns".

[21] though Reid et al. (2013) highlights a potential gap between the evaluation date and the actual data used in the evaluation, therefore the CRA intensity measure is created spanning a two-year window so that future-dated exams can be considered for contemporaneous MDI acquisitions- Also see the Appendix Table E.VI.

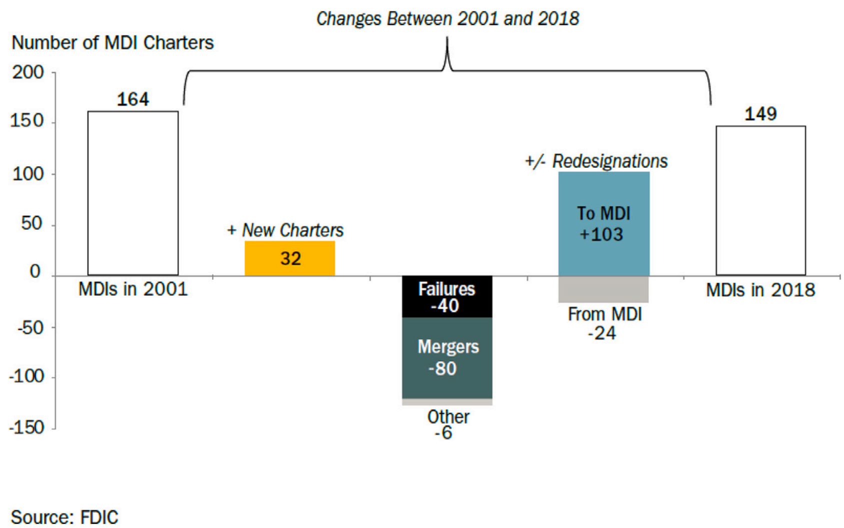


Fig. 7. Structural changes of MDIs.
This figures presents the structural changes in MDI charters from 2001–2018. Voluntary mergers are the greatest source of consolidation among MDIs over the last twenty years. *Source:* FDIC. https://www.fdic.gov/regulations/resources/minority/2019-mdi-study/full.pdf

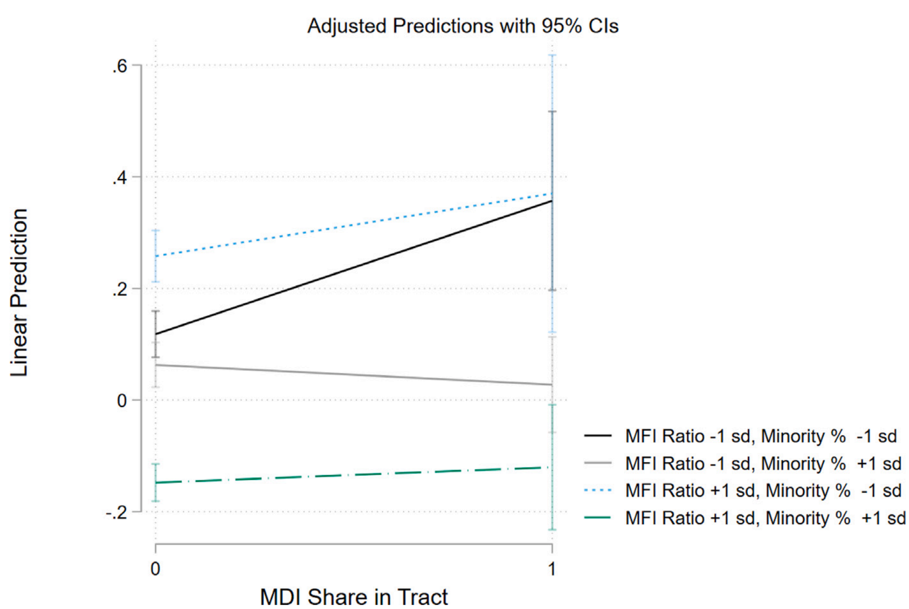


Fig. 8. Minority mortgage lending - MDI presence.
This figure plots the predictive margins for the following model:

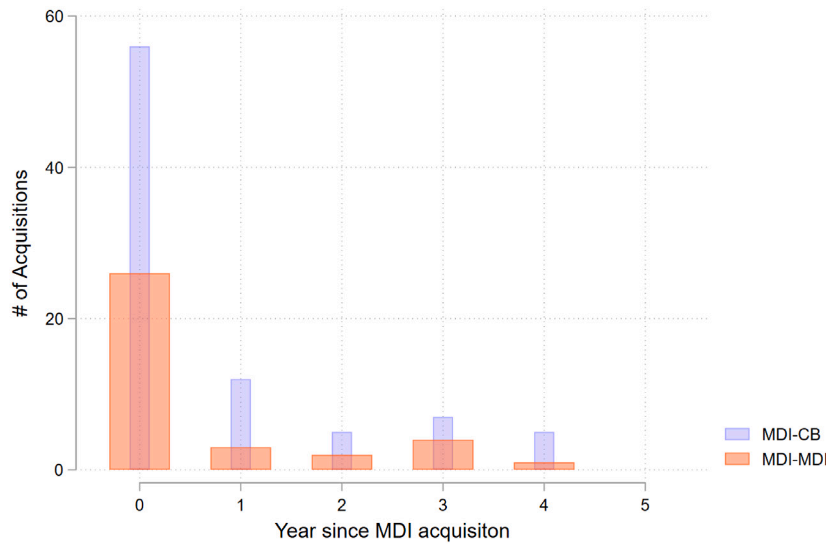
$$\begin{aligned} log(y_{i,t}^{minority}) = \; & \alpha + \beta_1 z\mathcal{S}_{i,t} + \beta_2 z\mathcal{R}_{i,t} + \beta_3 z\mathcal{M}_{i,t} + \beta_4(z\mathcal{S}_{i,t} \times z\mathcal{R}_{i,t}) + \\ & \beta_5(z\mathcal{R}_{i,t} \times z\mathcal{M}_{i,t}) + \beta_6(z\mathcal{M}_{i,t} \times z\mathcal{S}_{i,t})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

$z\mathcal{S}_{i,t}$, $z\mathcal{R}_{i,t}$ 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%.

is binding and future expansion is likely, acquiring an MDI can be a strategic, forward-looking move.

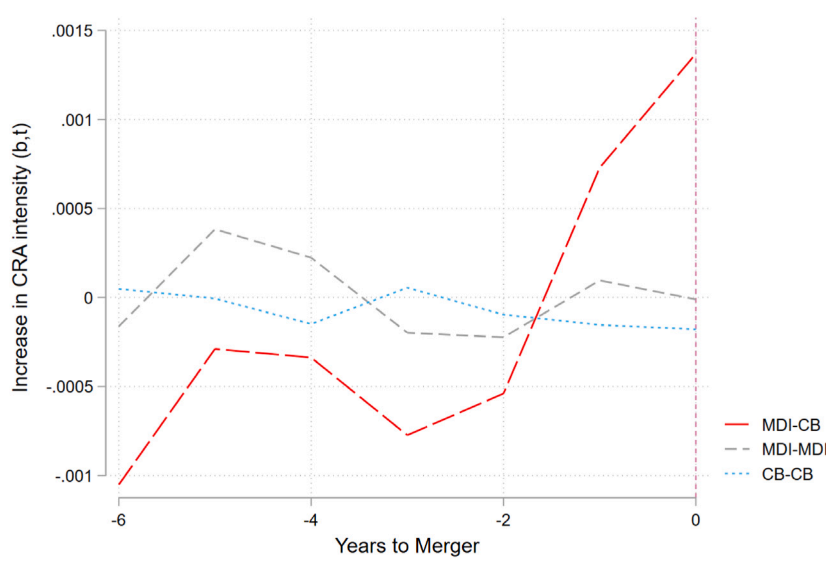
The exclusion restriction — that tract-level CRA intensity influences minority lending only through its effect on the likelihood of an MDI–CB merger — is supported by institutional features of the CRA framework and the design of the instrument. CRA evaluations are scheduled on fixed cycles (typically every 3–5 years) by federal regulators (OCC, FDIC, and the Federal Reserve) and are not triggered by local credit conditions. Tract-level variation in CRA intensity reflects exogenous changes in bank deposit shares (due to entry, exit, or failure), shifts in tract income from Census revisions, and OMB-driven metro reclassifications. These institutional features generate plausibly orthogonal variation in compliance pressure that is unrelated to unobserved changes in minority credit demand, satisfying the exclusion restriction. As a sanity check, the reduced-form estimates show that higher CRA intensity predicts lower minority lending—consistent with an indirect channel operating through symbolic MDI acquisitions rather than a direct credit expansion mechanism.

In sum, CRA intensity is both a strong predictor of MDI–CB mergers and plausibly exogenous to local lending trends. The instrument



(a) MDI Acquisitions within 5 Years

Blue: community banks; Orange: other acquirers.



(b) Acquirer CRA Intensity Change

Red: MDI-community bank; Grey: MDI-MDI; Blue: community banks.

Fig. 9. MDI Acquisitions and CRA Intensity.

captures preemptive, symbolic compliance behaviors without directly shifting credit supply, satisfying both inclusion and exclusion restrictions. To the extent the IV strategy is valid and cleanly identifies MDI–CB mergers, the next section describes the final baseline results in brief.

4.2.5. *Baseline results*

Results are presented in Table 3. Columns (1)–(4) present estimates relative to the MDI–MDI control group, and Columns (5)–(8) use tracts where the MDI landscape remained unchanged. Columns (2) and (6) present the OLS difference-in-differences estimates, while Columns (4) and (8) show the corresponding IV estimates. Columns (2) and (6) present difference-in-differences estimates with county-year fixed effects and thus reflect within-county identification. In contrast, Columns (1) and (5) include tract and year fixed effects, capturing variation both within and across counties. Columns (3) and (7) present reduced form IV estimates.

Across both control groups, I find economically large and statistically significant reductions in minority mortgage originations following MDI–Community bank mergers. Using the MDI–MDI control group, the IV estimate in column (4) suggests a post-merger decline of 0.37 log points, or approximately 31%. Using the no-change control group, the IV estimate in column (8) shows a larger decline of 0.64 log points, or about 47%. The corresponding OLS estimates, shown in columns (2) and (6), indicate declines of 0.33 log points (28%) and 0.33 log points (28%) respectively

Comparing the β_1 under the OLS and IV models, I find the usual case of the IV estimate ($\beta = -0.3731$) being about 25%–30% larger (Card,

Table 1
Summary statistics.

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	41 017.4	2843
Total equity capital ($ million)	114.2	367.4	18.8	−5.8	9.0	47.7	4 401.9	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	11 715.0	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	5 746.9	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	3 773.3	2842
Construction and development loans ($ Million)	47.5	59.0	30.1	−232.1	8.5	63.5	625.6	2842
1-4 family residential loans ($ Million)	135.2	167.0	96.6	−2249.8	29.6	186.0	3 220.1	2842
Multifamily home loans ($ Million)	41.3	81.5	20.0	−185.3	4.2	48.0	1 159.5	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	4 750.0	2843
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	47 364.8	101,770
Total equity capital ($ million)	30.4	67.6	14.5	−141.7	7.3	30.5	4 407.1	101,770
Core deposits (% of Total assets)	72.0	22.0	74.4	−5 624.0	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	2 387.5	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	7 871.0	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	−82 064.0	289.2	567.5	750 687.5	101,769
Commercial and industrial loans (% total risk capital)	85.0	327.8	67.4	−20 636.7	36.1	112.0	91 968.8	101,769
Non-farm non residential loans (% total risk capital)	154.9	920.6	128.0	−40 809.5	55.9	218.1	277 487.5	101,769
Construction and development loans (% total risk capital)	52.9	1185.6	26.7	−11 477.0	7.4	63.7	376 887.5	101,769
1-4 family residential loans (% total risk capital)	180.1	350.3	148.6	−21 500.7	80.7	240.0	96 312.5	101,769
Multifamily home loans (% total risk capital)	16.1	36.5	6.2	−1 070.3	0.0	19.6	4 401.5	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	−2 459.5	59.2	79.1	112 475.0	101,759

(*continued on next page*)

2001) than the OLS estimate ($\beta = -0.3292$) in MDI-MDI merger sample. In MDI-no change sample the IV estimates are larger likely due to synthetic event times in the control group. The first stage of the IV is significant and the IV ($\widehat{\text{Treat}_i \cdot \mathbf{Post}_t}$) predicts the interaction term ($\mathbf{Treat}_i \cdot \mathbf{Post}_t$) with a t-statistic of 8.23 (8.15 for MDI-no change sample) and slope coefficient of close to 1. The Sanderson and Windmeijer test for weak identification yields an F-statistic of 72.26 and 101.46 for the respective control samples, indicating strong first-stage and IV identification.

These findings provide the baseline for the deeper heterogeneity analyses that follow. In the next sections, I examine how these average effects vary by the pre-merger strength of the acquired MDI and the identity of the minority group served.

4.3. *Cross sectional results based on MDI heterogeneity*

4.3.1. *Based on pre-merger MDI performance*

In this section, I attempt to answer a central empirical question: Are all MDI losses equally detrimental for minority credit outcomes? There are plausible reasons to expect either direction of effect. On one hand, weaker MDIs — those with high loan losses or negative profitability — may still be serving credit-constrained households, extending credit that is negative NPV from the firm's perspective but socially beneficial.

Table 1 (*continued*).

Summary statistics - Mortgages ($ million) by MDI type								
Panel B-I								
Asian MDI								
Bank-Year	Mean	Std. Dev	Median	Min	P25	P75	Max	N
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

Summary statistics - Mortgages ($ million) by loan type								
Panel C-I								
MDI								
Bank-Year	Mean	Std. Dev	Median	Min	P25	P75	Max	N
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

(*continued on next page*)

Their acquisition by mainstream institutions could result in retrenchment, especially if acquirers restructure or downsize low-performing banks. On the other hand, it may be that declines are greatest when high-performing MDIs are acquired. These institutions may combine community mission with operational efficiency, supporting trust-based and culturally attuned lending strategies that are difficult to replicate. Their removal could represent the loss of an effective inclusion model.

Both views are grounded in different assumptions about how mission orientation interacts with institutional performance. If one believes inefficient MDIs are most impactful, then the concern is that acquirers will eliminate socially valuable lending that happens to be unprofitable. If one believes high-performing MDIs are more critical, the concern shifts to the erosion of sustainable models of inclusive finance—those that align social purpose with financial discipline. Determining which of these forces dominates is an empirical question.

Table 4 presents the results of the performance-stratified analysis, with separate panels for loan losses (Panel A) and profitability (Panel B). Each panel shows OLS and IV estimates across the lowest and highest quartiles of target MDI performance, using both MDI–MDI mergers and MDIs with no ownership change as control groups. The coefficients correspond to the post-merger change in minority mortgage originations in treated tracts.

The results reveal an asymmetry: the magnitude and significance of post-merger declines depend critically on the quality of the acquired MDI. Across both loan performance and profitability, credit declines are concentrated in the subset of tracts served by the most operationally

Table 1 (*continued*).

Summary statistics - Merger sample

Panel C-III - MDI-MDI Merger sample

Tract-Year Treated	Mean	Std. Dev	Median	Min	P25	P75	Max	N
CRA intensity	0.003	0.003	0.002	0.000	0.000	0.004	0.024	596
Minority loan amount (000s)	6771	15 823	2445	0	886	5870	217 994	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	4875	2061	4896	59	3390	5958	10,783	596
Minority percentage	53.6	29.0	53.9	4.1	29.0	80.0	98.8	596
MDI-MDI								
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	109 016	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	4817	1748	4762	1233	3643	5944	12,554	2240
Minority percentage	69.99	26.04	78.03	3.04	49.34	93.66	100.00	2240
MDI-No change								
CRA intensity	0.003	0.004	0.002	0.000	0.000	0.004	0.042	5140
Minority loan amount (000s)	6492	10 144	3555	0	1350	7718	237 101	5140
Households	1725	739	1641	0	1234	2130	6706	5140
MFI ratio	106.4	57.5	95.8	0.0	66.9	130.4	435.0	5140
Total bank branches	4	3	3	1	2	6	31	5140
Total MDI branches	1	1	1	0	0	1	11	5140
Total deposits	680,457	1,825,351	279,664	0	121,401	587,685	41,093,626	5140
Population	4731	2028	4443	0	3407	5878	16 532	5140
Minority percentage	65.51	26.06	72.06	0.00	45.72	89.31	100.00	5140

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.

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

	Log mortgages to minorities (1)	(2)	(3)	(4)	(5)
zMinority %	−0.1175***		−0.1526***	−0.1186***	−0.1166***
	(0.02)		(0.02)	(0.02)	(0.02)
zMFI ratio	−0.0170**	−0.0355***		−0.0153**	−0.0180**
	(0.01)	(0.01)		(0.01)	(0.01)
zMinority % × zMFI ratio	−0.0844***			−0.1215***	−0.0869***
	(0.01)			(0.01)	(0.01)
zMDI market share		−0.0011	0.0109*	0.0106	0.0099
		(0.00)	(0.01)	(0.01)	(0.01)
zMDI market share × zMFI ratio		−0.0038		0.0006	−0.0018
		(0.00)		(0.01)	(0.00)
zMDI market share × zMinority %			−0.0086***	−0.0103***	−0.0103***
			(0.00)	(0.00)	(0.00)
zMDI market share × zMFI ratio × zMinority %				0.0064**	0.0055**
				(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	No	Yes
Observations	298,019	298,019	298,,019	298,019	298,019
Adjusted R^2	0.8364	0.8361	0.8362	0.8329	0.8365

This table estimates the model in Eq. (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%. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3
Difference in differences and IV estimation.

	MDI-MDI				MDI-No change			
	Dif-Dif (1)	Dif-Dif (2)	Reduced form (3)	IV (4)	Dif-Dif (5)	Dif-Dif (6)	Reduced form (7)	IV (8)
Treated × Post	−0.2985	−0.3292***	−0.3422**	−0.3731**	−0.4152***	−0.3282**	−0.1743*	−0.6381***
	(0.19)	(0.09)	(0.15)	(0.14)	(0.14)	(0.16)	(0.10)	(0.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	Yes	No	No	No
County-Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	2351	1706	1277	1706	4430	4336	4340	4336
Adjusted R^2	0.7359	0.8083	0.8354	0.8452	0.7640	0.7942	0.8039	0.8098
SW F-Statistic	–	–	–	72.26	–	–	–	101.46

This table estimates the model in Eq. (2). The 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. In Columns (1)–(4), control tracts are those that experienced an MDI-MDI merger; in columns (5)–(8), the control tracts are those where MDIs experienced no ownership change. The main explanatory variables are the interaction of treated tracts with post-merger dummy (**Post**$_i$). All coefficients are normalized relative to the year prior to the merger event. Lagged tract-level controls include the 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 and reported in parentheses. All continuous variables are winsorized at 99%.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4
Loan losses and profitability.

Panel A: Target MDI loan performance								
	Relative to MDI-MDI mergers				Relative to MDI-No change			
	Lowest quartile		Highest quartile		Lowest quartile		Highest quartile	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Treated × Post	−0.5502***	−0.5345**	0.1039	−0.0172	−0.3938**	−0.4408**	−0.1425	−0.5261
	(0.14)	(0.24)	(0.18)	(0.17)	(0.17)	(0.18)	(0.35)	(0.50)
Observations	597	597	434	434	1340	1340	1186	1186
Adjusted R^2	0.8661	0.8989	0.8358	0.8259	0.7264	0.7801	0.7150	0.7365
SW F-Statistic	–	71.54	–	>999	–	>999	–	7.99
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
Panel B: Target MDI profitability								
	Relative to MDI-MDI mergers				Relative to MDI-No change			
	Lowest quartile		Highest quartile		Lowest quartile		Highest quartile	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Treated × Post	−0.1598	−0.2748	−0.3623*	−0.7615**	0.2803	0.1192	−0.3299**	−0.3606***
	(0.19)	(0.32)	(0.18)	(0.25)	(0.20)	(0.27)	(0.11)	(0.11)
Observations	532	532	582	582	1,100	1,100	1,027	1,027
Adjusted R^2	0.9083	0.8425	0.7417	0.8007	0.8994	0.8364	0.7848	0.8199
SW F-Statistic	–	72.86	–	390.50	–	110.80	–	>999
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

This table estimates the model in Eq. (2). The dependent variable is the log of mortgage originations to minorities. **Treated**$_i$ is an indicator equal to 1 if a census tract experiences an MDI–Community bank merger. The main explanatory variable is the interaction of **Treated**$_i$ with a post-merger indicator (**Post**$_i$). Results are stratified by target MDI loan performance prior to the merge.—Panel A by loan performance (net loan loss as a percentage of avg. total loans and leases), and Panel B by profitability (net operating income based ROA quartiles). Columns (1)–(4) compare to tracts affected by MDI–MDI mergers; Columns (5)–(8) compare to tracts with no ownership change. Each outcome is estimated using both OLS and IV methods. Regressions include tract and county-year fixed effects, and lagged tract-level controls: household count, minority share, MFI ratio, log deposits, HHI, lagged outcome, and branch count. Standard errors are clustered at the county level and are shown in parentheses. All continuous variables are winsorized at the 99th percentile.
* p < 0.10, ** p < 0.05, *** p < 0.01.

efficient MDIs—those with the lowest loan losses or highest profitability prior to the merger.

In Panel A, for example, IV estimates show a –0.53 log-point decline in originations ($p < 0.05$) when low-loss MDIs are absorbed, compared to MDI–MDI control tracts. The estimate is nearly identical (–0.44 log points) when the control group comprises MDIs with no ownership change. These effects translate to declines of approximately 41–53 percent in the volume of minority lending, depending on the control group. In contrast, when high-loss MDIs are acquired, the IV estimates are smaller in magnitude and statistically indistinguishable from zero, suggesting no measurable disruption to minority credit supply.

Panel B exhibits a similar pattern using pre-merger profitability as the stratifying dimension. The IV estimate in the highest-profit quartile is –0.76 ($p < 0.05$) relative to MDI–MDI controls, and –0.36 ($p < 0.01$) relative to MDIs with no change. These correspond to estimated declines of approximately 60 percent and 30 percent, respectively. Meanwhile, acquisitions of the least profitable MDIs show

Table 5
Heterogeneity by minority group.

Panel A: Relative to MDI-MDI mergers						
	Asian American		Hispanic		African & Native American	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Treated × Post	−0.1833**	−0.2615***	−0.9327***	−0.7541**	−0.1186	0.2155
	(0.07)	(0.08)	(0.21)	(0.29)	(0.14)	(0.16)
Observations	1301	1301	741	741	215	215
Adjusted R^2	0.7673	0.8255	0.8772	0.7939	0.9047	0.8839
SW F-Statistic	–	>999	–	37.97	–	716.73
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Relative to MDI No change						
	Asian American		Hispanic		African & Native American	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Treated × Post	−0.6022***	−0.5027***	−0.0914	−0.3239***	0.5705	0.5499
	(0.07)	(0.09)	(0.15)	(0.09)	(0.70)	(0.61)
Observations	2223	2223	1018	1018	234	234
Adjusted R^2	0.7264	0.8066	0.8069	0.8634	0.8773	0.8261
SW F-Statistic	–	13.43	–	71.09	–	9.87
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table estimates the model in Eq. (2) using minority-group-specific MDI-CB mergers. The dependent variable is the log of mortgage originations in a given tract-year. **Treated**$_i$ is an indicator equal to 1 if the tract experiences an MDI–Community bank merger. The sample is stratified by the identity of the merging MDI and analyzed separately by that group. Panel A uses tracts affected by MDI–MDI mergers as the control group. Panel B uses tracts where MDIs experienced no change in MDI ownership as control group. Each panel reports OLS and IV estimates of the post-merger treatment effect. Models include tract and county-year fixed effects, as well as lagged tract-level controls: household count, minority share, MFI ratio, log deposits, HHI, lagged dependent variable, and branch count. Standard errors are clustered at the county level and are shown in parentheses. Continuous variables are winsorized at the 99th percentile.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

no statistically significant effects, and point estimates are even slightly positive.

Together, these findings provide evidence that the loss of well-functioning, mission-oriented MDIs drive post-merger declines in minority credit access. When these institutions are taken over by acquirers lacking the same mission or local embeddedness, the result is a sharp withdrawal of mortgage credit to minority borrowers. By contrast, the acquisition of underperforming MDIs appears to have limited adverse consequences and may reflect efficiency-enhancing consolidation.

4.3.2. Heterogeneity by MDI type

There are four broad types of MDIs—Asian American, Hispanic, African American, and Native American. Asian and Hispanic MDIs together account for over 70% of all MDIs in the sample. In this section, I conduct subsample analyses limited to mergers involving only Asian American, Hispanic, or African/Native American MDIs to assess whether the effects of MDI loss differ by institutional identity. Table 5 reports these results using two different control groups: Panel A compares treated tracts to those experiencing MDI–MDI mergers, while Panel B uses tracts where MDIs experienced no ownership change.

In Panel A (relative to MDI-MDI control group), across both OLS and IV specifications, the loss of Asian American MDIs results in a more modest decline in minority mortgage originations. Specifically, the OLS estimate shows a 16.7% reduction (–0.18 log points, statistically significant) and the IV estimate shows a 23.0% reduction (–0.26 log points, statistically significant). On the other hand, the loss of Hispanic MDIs leads to a larger decline in minority mortgage originations. The OLS estimate indicates a 60.6% reduction (–0.93 log points, statistically significant) and the IV estimate shows a 53.2 reduction (–0.75 log points, statistically significant). Compared to the baseline estimates reported earlier, Hispanic MDIs exhibit a larger decline, while Asian American MDIs experience a smaller decline when using the MDI-MDI control group.

In Panel B (Relative to MDI-No Change control group), the results differ. For Asian American MDIs, the IV estimate shows a 45.3% decline (–0.60 log points, statistically significant), and the OLS estimate shows a 39.6% decline (–0.50 log points, statistically significant). In contrast, the loss of Hispanic MDIs results in a smaller decline. The IV estimate shows a 27.7% reduction (–0.32 log points, statistically significant), while the OLS result is small and statistically insignificant (–0.09 log points). In this case, Hispanic MDIs exhibit a smaller decline compared to the baseline in Panel A, while Asian American MDIs show a more significant decline than the baseline.

For African and Native American MDIs, the estimates in both panels are statistically indistinguishable from zero: –0.12 log points (OLS) and +0.21 log points (IV) in Panel A; +0.57 log points (OLS) and +0.55 log points (IV) in Panel B. This likely reflects smaller sample sizes and more diffuse institutional coverage.

The stronger declines associated with Hispanic MDIs in the MDI–MDI comparison may reflect greater vulnerability among their borrower base. Hispanic MDIs frequently serve first-generation borrowers who face unique barriers to credit access and are more reliant on culturally tailored underwriting practices. The removal of these practices under new ownership may therefore generate sharper disruptions. By contrast, Asian American borrowers typically have higher median household incomes, better credit scores, and greater access to mainstream banking alternatives. According to the 2020 ACS and HMDA reports, Asian households report higher rates of homeownership, higher loan approval rates, and greater use of conventional mortgage products. This may partly explain why the loss of an Asian MDI results in (though statistically significant and non-trivial) smaller credit disruptions. Since both control tracts also offer natural event timelines due to an actual MDI-MDI event, the comparison is consistent.

Interestingly, the gap in treatment effects narrows — or reverses — when non-merging MDIs serve as the control. This difference likely reflects the relative strength of the control group itself: Asian MDIs that

Table 6
Effect of branch closures and branch changes on minority originations.

	Relative to MDI–MDI					Relative to MDI–No change	
	(1) PM Closure vs. PM Closure	(2) PM Closure vs. Ownership Chg.	(3) Ownership Chg. vs. Ownership Chg.	(4) PM Closure vs. Reg Closure	(5) Ownership Chg. vs. Reg Closure	(6) PM Closure vs. No Change	(7) Ownership Chg. vs. No Change
Panel A: OLS estimation							
Treated × Post	−0.2323*	−0.4582***	−0.2642**	−0.2877*	−0.1898	−0.9158***	−0.3886*
	(0.12)	(0.05)	(0.12)	(0.15)	(0.21)	(0.11)	(0.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359	402	325	359	386	2991	2833
Adjusted R^2	0.8268	0.9162	0.9000	0.7847	0.6690	0.8071	0.8185
Panel B: Instrumental Variables (IV) estimation							
Treated × Post	−0.1468	−0.5299***	−0.3024**	−0.3204*	−0.3585**	−0.5617**	−0.5183*
	(0.17)	(0.10)	(0.12)	(0.18)	(0.18)	(0.24)	(0.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359	402	325	359	386	2991	2833
Adjusted R^2	0.8910	0.8817	0.7949	0.8406	0.8188	0.8706	0.8491
SW F-Statistic	704.18	436.48	>999	328.29	394.33	156.94	149.38

This table estimates the model in Eq. (2). The dependent variable is the log of mortgage origination to minorities. **Treated** is an indicator equal to 1 if the census tract experiences an MDI–Community bank merger. Columns (1)–(5) use tracts affected by MDI–MDI mergers as the control group. Columns (6)–(7) use MDIs with no ownership change. "PM Closure" refers to post-merger branch closures resulting from MDI–Community bank mergers. "Reg Closure" refers to branch closures in the normal course of business (i.e., not merger-related). Regressions include tract and county-year fixed effects, lagged tract-level controls, and standard errors clustered at the county level. Continuous variables are winsorized at the 99th percentile.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

remain independent are generally more profitable and operationally stable than their Hispanic counterparts. This stronger benchmark inflates the measured treatment effect for Asian MDI mergers in Panel B. Conversely, the weaker control group for Hispanic MDIs dampens the relative decline. However, it must also be noted that the synthetic merger event timeline in the control tract could also be a contributing confounding factor. Although these interpretations are consistent with observed institutional patterns, borrower-level data would be required to confirm the precise behavioral and market mechanisms, and the inferences drawn above should be interpreted with caution.

5. Channels of minority credit supply decline

Following an MDI–CB merger, a local neighborhood may experience one of two outcomes: either the MDI branch physically closes down, or it continues operations as a non-MDI branch under new ownership. Depending on the outcome, the impact on local minority credit supply will differ. While both scenarios disrupt the original lending relationship, the presence of a physical branch under new ownership may preserve some continuity via geographic proximity and partial staff retention. However, when a branch physically shuts down, both geographic and cultural proximity are lost. Frictions in forming new lending relationships (Argyle et al., 2020) and the abrupt loss of embedded borrower–lender ties (Drexler and Schoar, 2014) likely exacerbate the decline in credit supply.

To examine this, I construct a national panel of branch-location pairs by combining the FDIC's Summary of Deposits with a geo-coded address locator. This allows me to observe the post-merger status of each MDI branch and to distinguish between (i) tracts that experience post-merger branch closures and (ii) those where the branch remains open but changes ownership. I re-estimate Eq. (2) within these subsamples.

Table 6 presents the results. Columns (1)–(5) use MDI–MDI mergers as the control group, while columns (6)–(7) uses MDI-no change control group. A priori, the expected magnitude of lending decline varies by scenario. Each column captures a distinct scenario based on whether the MDI branch closed following the merger (Post Merger Closure or PM merger), remained open under new ownership (Ownership Change), or underwent a regular, non-merger-related closure (Reg Closure). Regular closures are defined by restricting control group tracts to only those that only experienced closures prior to the merger event.

In Column (1), both treated and control tracts experience post-merger closure. A priori, the expected direction of the effect is unclear. On one hand, both groups lose physical presence and mission, which should theoretically cancel out. On the other, if the acquiring institution's identity influences post-closure community engagement or future lending strategy, a difference may still emerge. The coefficient of −0.23 log points (≈ 21% decline; not statistically significant) could cautiously be interpreted to suggest that closures post Community Bank acquisitions are more disruptive.

Column (2) compares post-merger closures to post-merger ownership changes. Here, one expects a larger decline due to the joint loss of mission and proximity in the treated group versus mission loss alone in the control. The coefficient is −0.46 log points (≈ 37% decline; $p < 0.01$), the largest and most precisely estimated in the table. Column (3) compares ownership changes in both groups, differing only in acquirer identity. The resulting coefficient is −0.26 log points (≈ 23% decline; $p < 0.05$), suggesting that mission loss, even without physical withdrawal, has substantial consequences. The ratio of the percent changes in Columns (3) and (2)—23% divided by 37%—implies that the impact of mission loss alone accounts for approximately 62% of the total effect observed when both mission and proximity are lost.

In Columns (4) and (5), I compare merger-induced outcomes to regular branch closures. Column (4) (−0.29 log points; ≈ 25% decline; $p < 0.1$) indirectly validates the combined effect of mission and proximity loss, and offers an alternative benchmark to Column (2). Tentatively, the ratio of the percent changes in Column (4) to Column (2)—25% divided by 37%—suggests that about 68% of the total lending loss observed in Column (2) could be attributable to the general effect of closure, while the remainder may reflect MDI-specific merger dynamics.

Column (5) is the most ambiguous scenario: the treated group loses only mission, while the control group loses both mission and physical presence, though not due to merger. The coefficient (−0.19 log points;

Table 7
Minority home-ownership percentage - ACS - 1 yr.

	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

This table estimates the following model:
$\mathcal{M}_{c,t} = \alpha_c + \gamma_{m,t} + \beta_1 S_{c,t-1} + \beta_1 X_{c,t-1} + \epsilon_{c,t}$,
The dependent variable $\mathcal{M}_{c,t}$ is percentage minority home-ownership in year t in a county c. The main explanatory variable is $S_{c,t-1}$, 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%.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8
Household home-ownership transition probability.

	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	9013
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

This table estimates the following model:
$(\mathcal{O}_{h,c,t-1,t} = 1) = \alpha_c + \gamma_{m,t} + \beta_1 S_{c,t-1} + \beta_2 \theta_{h,c,t-1} + \beta_2 X_{c,t-1} + \epsilon_{c,t}$
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 $S_{c,t-1}$, 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%.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

≈ 17% decline; not statistically significant) is smaller in magnitude and more difficult to interpret, suggesting that selection or unobserved differences in the nature of closures may be at play.

Columns (6) and (7) compare post-merger changes to tracts where the MDI remained independent. These offer the cleanest contrast between mission retention and loss. PM closures are associated with a −0.92 log point decline (≈ 60% decline; $p < 0.01$), while ownership changes show a −0.39 log point decline (≈ 32% decline; $p < 0.1$). The ratio of the percent changes in Columns (7) and (6)—32% divided by 60%—implies that approximately 53% of the total observed effect when both proximity and mission are lost may be attributed to mission loss alone.

Overall, the findings confirm the a priori expectation that both mission and proximity matter for sustaining minority lending, and that

Table 9
Effect of branch closures and branch changes on minority denials.

	Relative to MDI–MDI					Relative to MDI–No Change	
	(1) PM Closure vs. PM Closure	(2) PM Closure vs. Ownership Chg.	(3) Ownership Chg. vs. Ownership Chg.	(4) PM Closure vs. Reg Closure	(5) Ownership Chg. vs. Reg Closure	(6) PM Closure vs. No Change	(7) Ownership Chg. vs. No Change
Panel A: OLS estimation							
Treated × Post	0.0232	0.0507	0.1155	0.0705	0.1106	0.0801	0.1030
	(0.10)	(0.05)	(0.10)	(0.12)	(0.10)	(0.06)	(0.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	307	351	300	298	338	2,532	2,423
Adjusted R^2	0.4377	0.4540	0.8370	0.5009	0.8393	0.5384	0.4929
Panel B: Instrumental Variables (IV) estimation							
Treated × Post	0.0475	0.0629	0.1133	0.1260	0.1304	−0.1756	0.1922*
	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)	(0.35)	(0.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	307	351	300	298	338	2,532	2,423
Adjusted R^2	0.6709	0.6692	0.6824	0.7839	0.7006	0.0648	0.0452
SW F-Statistic	>999	>999	>999	867.77	108.99	4.42	90.34

This table estimates the model in Eq. (2). The dependent variable is the **minority loan denials as a fraction of total denials.** **Treated** is an indicator equal to 1 if the census tract experiences an MDI–Community bank merger. Columns (1)–(5) use tracts affected by MDI–MDI mergers as the control group. Columns (6)–(7) use MDIs with no ownership change. "PM Closure" refers to post-merger branch closures resulting from MDI–Community bank mergers. "Reg Closure" refers to branch closures in the normal course of business (i.e., not merger-related). Regressions include tract and county-year fixed effects, lagged tract-level controls, and standard errors clustered at the county level. Continuous variables are winsorized at the 99th percentile.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

their combined loss leads to the steepest declines. The consistency of the implied ratios across independent control groups is reassuring, suggesting that mission loss alone accounts for more than half (average of 53% and 62%) of the observed decline when both factors are jointly removed.

6. MDI's effect on minority homeownership

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 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 one-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:

$$\mathcal{M}_{c,t} = \alpha_c + \gamma_{m,t} + \beta_1 \mathcal{S}_{c,t-1} + \beta_1 X_{c,t-1} + \epsilon_{c,t}. \tag{6}$$

The dependent variable $\mathcal{M}_{c,t}$ is percentage minority homeownership in year t in a county c. It is 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. Table 7 presents the results.

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 7. 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,[22] the racial homeownership gap in 2019 was at its peak at about 31.2%. By one estimate,[23]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 CPS. 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:

$$(\mathcal{O}_{h,c,t-1,t} = 1) = \alpha_c + \gamma_{m,t} + \beta_1 \mathcal{S}_{c,t-1} + \beta_2 \theta_{h,c,t-1} + \beta_2 X_{c,t-1} + \epsilon_{c,t}. \tag{7}$$

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 8. For every 1% increase in the market

[22] https://www.census.gov/programs-surveys/ahs/data.html.
[23] https://www.urban.org/urban-wire/breaking-down-black-white-homeownership-gap.

Table 10
Moderation effect of pre-merger branch capacity.

Panel A: Below median pre-merger branch share					
	Mortgage originations to minorities				
	(1) PM Closure vs. PM Closure	(2) PM Closure vs. Ownership Chg.	(3) Ownership Chg. vs. Ownership Chg.	(4) PM Closure vs. Reg Closure	(5) Ownership Chg. vs. Reg Closure
Treated × Post	0.0379	−0.8209***	−0.3489***	−0.3768	−0.3267
	(0.82)	(0.28)	(0.07)	(0.28)	(0.22)
Controls	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	191	201	106	134	128
Adjusted R^2	0.7933	0.8238	0.7962	0.6963	0.7377
Panel B: Above median pre-merger branch share					
	Mortgage originations to minorities				
	(1) PM Closure vs. PM Closure	(2) PM Closure vs. Ownership Chg.	(3) Ownership Chg. vs. Ownership Chg.	(4) PM Closure vs. Reg Closure	(5) Ownership Chg. vs. Reg Closure
Treated × Post	0.3203	−0.1181	−0.0717	−0.3916	−0.2204
	(0.28)	(0.28)	(0.28)	(0.35)	(0.30)
Controls	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	95	128	143	132	164
Adjusted R^2	0.8734	0.8246	0.7094	0.7052	0.6567

This table estimates the model in Eq. (2). The dependent variable is the **log of mortgage originations to minorities**. "Treated" is an indicator equal to 1 if the census tract experiences an MDI–Community bank merger. Columns (1)–(5) use tracts affected by MDI–MDI mergers as the control group. "PM Closure" refers to post-merger branch closures due to MDI–Community bank mergers. "Reg Closure" refers to closures unrelated to mergers. Regressions include tract and county-year fixed effects, lagged tract-level controls, and standard errors clustered at the county level. Continuous variables are winsorized at the 99th percentile. Panels split the sample by whether the pre-merger branch's deposits are above or below the median.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

7. Additional tests

This section presents two additional tests designed to probe the mechanisms behind the decline in minority lending following MDI–Community bank mergers. Both examine different dimensions of how mission-driven institutions connect with borrowers: the first focuses on borrower behavior, asking whether reduced originations reflect disengagement rather than tighter underwriting; the second tests whether effects are concentrated in areas served by smaller, more community-embedded branches or are equally present in areas served by larger, potentially more resilient institutions. Taken together, these analyses assess the role of trust-based, local lending relationships as a core channel through which MDI takeovers reshape credit access.

7.1. Minority denial rate effects

The first test evaluates whether the observed decline in minority mortgage originations reflects borrower disengagement or a tightening of loan underwriting standards. This distinction matters for interpretation: if acquirers systematically deny more applications, the effect stems from formal credit rationing; if fewer applications are submitted to begin with, the mechanism reflects disengagement due to diminished trust or outreach.

A priori, both are possible. On the one hand, the acquiring bank may impose stricter underwriting, which could lead to a higher denial rate of minority applications following the merger. On the other hand, if the MDI had been pursuing a push-based model—recruiting applications from marginal borrowers, accepting nontraditional collateral, and relying on trust—the end of such engagement could discourage applications without changing formal approval behavior. [24]

To assess this, Table 9 reports estimates where the dependent variable is the fraction of total minority denials in a tract-year.

Across IV and OLS estimates, columns (1) through (7), the estimated effects are statistically insignificant, although they are mostly positively skewed. It cannot be concluded with certainty that minority denial rates rise after the merger. The results are instead more consistent with the borrower disengagement mechanism when the mission-oriented structure of the MDI is lost.

7.2. Moderation by pre-merger branch size

The second test assesses whether the decline in minority lending is more pronounced in areas served by smaller, more localized branches. While the direction of the effect is ambiguous a priori—smaller branches may be more fragile, but larger ones may be more disruptive when lost—the data reveal a clear asymmetry.

To test this, I re-estimate the main specification using subsamples based on whether the affected MDI branch had an above- or below-median share of county deposits. Due to small sample sizes of the

[24] This view is supported by the FDIC's guidance on MDI collaboration, which describes MDI strategies as reliant on outreach, flexibility, and deep community ties. https://www.fdic.gov/regulations/resources/minority/collaboration/resource-guide.pdf A related study by the National Bankers Association finds that MDI lending during 2019–2022 targeted underserved communities using tailored, proactive engagement. https://www.nationalbankers.org/research-resources.

sub-samples, IV estimates will suffer from finite-sample bias and are unreported (see Table 10)

A clear pattern emerges: declines in minority mortgage originations are concentrated in tracts served by smaller branches. In column (2) of Panel A, originations decline by 56% (0.82 log points) relative to similar tracts affected by ownership changes without closure. In column (3), the decline is 29% (0.35 log points) for ownership changes only. In contrast, tracts served by larger branches (Panel B) show no statistically significant change across any specification.

These results suggest that smaller branches — often more embedded in the community and more reliant on relationship-based lending — are especially vulnerable during mergers. When a mission-driven MDI is taken over, smaller operations may be more likely to shut down, consolidate, or lose the flexible underwriting practices that helped serve first-time or financially inexperienced borrowers. Larger branches, by contrast, may be more likely to survive the transition intact.

The ratio of the effects in column (3) to column (2) — roughly one-half — also mirrors the pattern seen in the full sample: more than half the total decline appears driven by the loss of mission rather than by physical branch closure alone.

8. Conclusion

MDIs represent a unique partnership between the market, the state, and underserved communities. I quantify their impact using tract-level data and find that minority credit supply declines sharply and persistently following the loss of an MDI. I address potential demand confounding factors and identify post-merger mission loss as a key channel. MDIs also play an important role in narrowing the home-ownership gap. However, their benefits come with operational costs, as many are inefficient and vulnerable to failure. My findings indicate that the most efficient MDIs account for the majority of the credit gains, suggesting that preserving these high-performing institutions is particularly crucial.

These results underscore the need to protect the MDI ecosystem. Policymakers should more closely oversee non-assisted mergers that risk eliminating effective mission-driven lenders. A promising avenue for future research is whether financial technology can help scale inclusive credit models, or whether it accelerates mission drift.

CRediT authorship contribution statement

Prithu Vatsa: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfi.2025.101163.

Data availability

Data will be made available on request.

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Further reading

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