Location Choices of Community Banks and Redlining: The case of Minority Depository Institutions

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Abstract

I study the proximity of mission-oriented community banks, Minority Depository Institutions to historically segregated urban areas that faced restricted mortgage activity. To achieve this, I construct a panel dataset and apply a Poisson Generalized Estimating Equation (GEE) framework to investigate whether MDIs are more likely to locate in historically redlined urban areas, based on Home Owners' Loan Corporation's (HOLC) "residential security maps" when compared to non-MDIs. I find Black MDIs are 9 percent more likely to locate in census tracts for each one point increase in their HOLC scores whereas non-MDI bank branches are 10 percent less likely to locate in census tracts for each one point increase in their HOLC scores. The findings indicate how historical federal policies still shape credit markets and how Black MDIs co-exist with larger banks in their current local markets.

JEL Classification Codes: G20, G21 , L10

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1 Introduction

The per capita wealth ratio between Whites and Black currently stand at six to one. Derenoncourt et al. (2024) document the role income growth, savings behavior, and capital returns play in explaining the gap and show from a starting point of nearly 60:1 per capita wealth ratio following the Civil War, the white-to-Black per capita wealth ratio fell to 10:1 by 1920 and to 7:1 by the 1950s, only to fall to 6:1 in the present day. One of the persistent reasons behind the enduring wealth gap is the difference between ownership rates and home values among Blacks and White; Aaronson et al. (2021) show how specific federal government agencies established during the 1930s reduced home ownership rates, home values, and rents and increased urban racial segregation in later decades.

The enduring wealth gaps is partially due to New Deal era federal agencies such as the Home Owner's Loan Corporation (HOLC)and the Federal Housing Administration (FHA) established in 1933 and 1934 respectively. These institutions were designed to facilitate the refinancing and insuring nonfarm residential mortgages after the Great Depression. In the late 1930s, HOLC created color-coded maps that evaluated neighborhoods in more than 200 cities and exacerbated restricted mortgage activity in certain neighborhoods. By color coding urban neighborhoods, the HOLC maps highlighted existing economically impoverished areas which lead to further capital disinvestment because mortgages were not being insured in these areas (Jackson, 1985). Interestingly enough, due to "porous boundaries between public and private" institutions, the color-coded investment risk maps created by the HOLC were strongly reliant on private realtors and appraisers at the time for neighborhood information (Winling and Michney, 2021). Aaronson et al. (2021) and Akbar et al. (2025) find that the HOLC maps had consequential and lasting effects on the development of urban neighborhoods in the following decades through reduced credit access and subsequent disinvestment in these neighborhoods while also eroding the wealth of their residents, as a result of falling property values.

Access to credit is a critical driver of economic growth and stability in local commu-

nities, however, the effects of the HOLC security maps on access to credit persists in the present. Woods (2012) show the maps systematically disadvantaged low-income and minority city-dwelling residents and worsened the disproportionately substandard urban housing conditions for these urban communities. Hernandez (2009) studies the Sacramento county specifically and show that a substantially large portion of mortgage application denials, along with subprime mortgage borrowers and property foreclosures during the Great Recession were concentrated in urban regions that were previously designated as "declining" and "hazardous" and graded D by the HOLC maps. Park and Quercia (2020) find four out of five neighborhoods graded A by the HOLC maps are high income at present and none are low income, whereas over half of neighborhoods graded C and D are low income. They further show these neighborhoods face lower economic mobility and have a higher mortgage default rates even after controlling for neighborhood income. Hynsjö and Perdoni (2022) find a sizable reduction in property values, home values and home ownership rates in neighborhoods with the lowest grade along with an increase in the share of Black residents with the negative effects on property values persisting until the early 1980s, a finding supported by Joshi et al. (2024) who analyze more recent data.[1] Meanwhile, Anders (2023) uses an unannounced population cutoff that determined which cities were redlined and show that the HOLC redline maps increased present-day city level crime. The author further uses a spatial regression discontinuity to identify mechanisms through which redlining influenced the present-day neighborhood level distribution of crime in Los Angeles, California.

This paper studies the location choices of depository institutions, known as Minority Depository Institutions (MDIs) and whether these institutions have a higher likelihood of locating in neighborhoods with lower HOLC grades when compared to non-MDIs. MDIs are US banks owned and operated primarily by minorities and established to serve minority borrowers that historically had restricted access to credit.[2] The Federal Deposit Insurance Corporation (FDIC) defines MDIs as banks serving primarily minority-populated areas, with

1. Their dataset spans from 2000 until 2018.
2. Government Accountability Office, GAO (2006) report

at least 51% minority ownership or with a majority of the board of directors who are of minority origin.[3] Since MDIs are mission-driven community banks primarily owned by minorities, I study whether they establish in neighborhoods with a history of restricted credit access and uninsured mortgages and examine their proximity to such neighborhoods as reflected in the HOLC's "residential security maps".

To conduct the research, I construct panel datasets using National Bureau of Economics Research's (NBER) Tract Distance Database to locate neighboring tracts, FDIC's Summary of Deposits, HOLC redlining scores [4] and percentages of different grades ("A, B, C, D") within the census tracts under study and their neighboring tracts and the 5 year American Community Surveys (ACS). The studied tracts are those with bank branches in counties with MDIs. I create a balanced panel with 12,953 census tracts with bank branches observed over 11 years, 2011 until 2021. Among them about 1090 census tracts contain MDIs.

For the primary analysis, I construct two sets of data, one with features of all neighboring tracts within a mile of the census tracts under study and one with features of all neighboring tracts within 5 miles of the census tracts under study. The outcome variables are the number of Black MDIs, Asian MDIs, Hispanic MDIs and non-MDIs in the studied tracts. I estimate the models using Poisson Generalized Estimating Equations (GEEs) following Wang et al. (2024). I use population counts at the census tract level and within the neighboring tracts, percent of the minority sharing the minority identity with the MDI owners, status of the tracts as low or moderate income (LMI) [5] among others as explanatory variables.

I find an increase in a tract's HOLC or redlining score increases the likelihood that of a Black MDI locating in that tract. Conversely, I find an increase in the HOLC score will

3. Minority-owned banks represent a very small percentage of depository institutions in the US. MDIs consist of 2.8 percent of all depository institutions in the US and the combined assets of $330 billion of the 147 MDIs (in 2024) represents just 1% of U.S. bank assets (Barth and Xu, 2020; Toussaint-Comeau and Newberger, 2023).
4. I use data on historic HOLC redlining scores for the 2010 census tracts developed by Meier and Mitchell (2023) using percentages of HOLC areas in each tract. The data is hosted on the Inter-university Consortium for Political and Social Research's (openICPSR) website.
5. The Department of Housing and Development (HUD) considers U.S. Census Tracts in which 51 % or more of the households earn less than 80 percent of the Area Median Income (AMI) as LMI tracts. AMI is the median household income for a specific geographic area (e.g., county, metropolitan area).

decrease the likelihood of a non-MDI locating in the tract. To be precise, Black MDIs are 9 percent more likely to locate in census tracts for each one point increase in their HOLC scores. Similarly, non-MDI bank branches are 10 percent less likely to locate in tracts for each one point increase in their HOLC scores. The results hold when I consider neighboring tracts within both 1 mile and 5 miles radius of the studied tracts. Asian and Hispanic MDIs do not locate in census tracts with higher HOLC scores, although Black MDIs, Asian MDIs and non-MDIs do tend to locate near census tracts with higher HOLC scores. Hence, I find Black MDIs are 18-30 percent more likely to locate in tracts for each one point increase in the average HOLC scores of their neighboring tracts and non-MDIs are 11-18 percent more likely to locate in tracts for each one point increase in the average HOLC scores of their neighboring tracts. Hispanic MDIs, on the other hand, are 25-50 percent less likely to locate in tracts for each one point increase in the average HOLC scores of their neighboring tracts while for Asian MDIs do not show any consistent results either at the census tract level or within the surrounding tracts.

For robustness, I use the percent of the lowest HOLC grade, Grade D as an explanatory variable in separate estimations. The results are largely similar. Black MDIs are 4-8 percent more likely to locate in tracts for each ten percentage point increase in tract area with Grade D. In other words, holding all other control variable constant, including the number of non-MDIs branches and the status of the tracts as low-middle-income, Black MDIs are more likely to locate in census tracts with more redlining. While non-MDIs bank branches are 4-5 percent less likely to locate in tracts for each ten percentage point increase in tract area with Grade D. At the same time, Black MDIs are 13-19 percent more likely to locate in tracts for each ten percentage point increase in graded D areas within their neighboring tracts, and non-MDIs are 7-9 percent more likely to locate in tracts for each ten percentage points increase in graded D areas within their neighboring tracts

The paper draws on literature that study location choices of businesses, especially bank branches. Chang et al. (1997) find bank branches have a tendency to spatially cluster and

attribute this behavior to rational herding by banks. They also find after controlling for the expected profitability of operating a branch in an area, branches tend to open in locations with existing branches, even though it leads to less profitability among branches. Ho and Ishii (2011) estimate a spatial model of consumer demand for retail bank deposits that accounts for consumer disutility from distance traveled. They show a large gain in consumer surplus due to the passage of Riegle–Neal Act in 1994, which allowed banks to operate branches across state lines. The legislation removed barriers to interstate banking causing new bank branches to open in markets with existing branches. Babajanova (2022) show MDIs that locate in low and moderate income (LMI) tracts or share a location with a rivalrous MDI or a non-MDI branch have lower profits while a larger local population leads to higher profit levels for MDIs. My findings show MDIs tend to cluster in areas with higher percentages of populations sharing the same minority identity as the MDI ownership and close to other non-MDIs, even though they serve different demographics and customer bases, consistent with the findings of Chang et al. (1997) and Babajanova (2022).

The paper also builds upon prior literature on the historical segregation of urban areas, the racial wealth gap between Whites and Blacks and credit access within minority communities. Previous research by Aaronson et al. (2021) focus on the enduring effects of the HOLC maps resulting in reduced home ownership rates, house values, and rents and exacerbated racial segregation in the following decades. Akbar et al. (2025) use a city block level dataset of matched addresses, and find that over a single decade, (between 1930 and 1940) rental prices soared by roughly 50% on city blocks that transitioned from all white to majority black, while, home values fell by 10% relative to blocks that remained all white. Hernandez (2009) studies the housing crisis during Great Recession and finds a significantly higher concentration of subprime mortgage activity and property foreclosures in non-white, previously redlined residential settlements in Sacramento, California. Park and Quercia (2020) show urban neighborhoods rated declining or hazardous in the 1930s are still associated with poorer economic conditions eight decades later.

Finally, my paper contributes to research studying MDIs and their impacts on their immediate communities. Breitenstein et al. (2014) and Eberley et al. (2019) show the markets served by MDI offices include a higher share of population living in low-or-moderate-income (LMI) census tracts, as well as a higher share of minority populations. Similarly, Hurtado and Sakong (2023) show minority borrowers applying for mortgages in banks sharing minority identity are nine percentage points more likely to be approved than otherwise identical minority borrowers in non-minority banks. They also show a minority loan officer is six times more likely to approve mortgages applications with similar racial heritage. Toussaint-Comeau et al. (2020), who study MDI failures during the Great Recession, show small businesses in primarily black census tracts faced significant frictions in obtaining credit as a result of the failures, leading to cumulative declines in aggregate small business lending in black neighborhoods that lasted up to 3 years. Similarly, Razzak (2025) studies closures of MDI bank branches within census tracts and show how closures of Asian MDI branches lead to a 20-24% decrease in large-sized mortgage originations within among Asians and closures of Hispanic MDI branches reduces small business lending to small firms (less than $1 million in assets) by 13% within their immediate communities.

In this paper, I combine the three sets of literature and study whether MDIs locate in urban neighborhoods that have been historically redlined. Economic and social outcomes of communities are strongly correlated with their ability to access credit. A reliable avenue towards credit accessibility may be as simple as how close a household or small business is to a bank branch (Nguyen, 2019; Herpfer et al., 2022). This is the first paper to study the location choices of MDIs, especially Black banks and how these choices may be influenced by historical factors, such as the redlining of urban neighborhoods during the New Deal era.

2 Institutional and Historical Context

This section provides a historical grounding for my paper as I discuss the interplay between the HOLC maps, the residents within the redlined neighborhoods, their reduced access to credit and how the need for this access initially facilitated the formation of Black

banks within these neighborhoods. The aim of the paper is to understand whether MDIs serve historically redlined tracts in greater proportion when compared to non-MDIs, provided bank branches (MDI and non-MDI branches) exist in clusters.

In the 1930s, the HOLC maps graded urban neighborhoods using letters, A, B, C and D. Urban neighborhoods coded green (designated as A) were considered "new, homogeneous, and in demand as residential locations in good times and bad times.", while areas coded blue (designated as B) were termed "reached their peak", but were "still desirable". Finally, areas coded yellow (designated as C) were termed as "definitely declining" and those coded red (designated as D), the lowest rating, were considered as areas "in which the things taking place in C areas have already happened" (Jackson, 1985). Even prior to the HOLC color coded maps, the FHA evaluated neighborhoods using block level information provided by the New Deal relief programs and the US Census. The agency did not insure mortgages in areas shaded red (or graded D) where a majority of urban Black Americans resided; these were also low income neighborhoods in the cities (Fishback et al., 2022). Because HOLC maps served as a dominant source of information for private lenders, the HOLC and the FHA restricted the geographic scope of their mortgage activity and perpetuated racially based discriminatory lending (Rothstein, 2018; Glotzer, 2020).

Prior to the development of these maps, the Great Migration caused Blacks to leave southern states and migrate into the major urban regions in the mid-west and eastern parts of the US, resulting in substantial real estate development following World War I, with disorderly immigration, industrialization and urban growth. As early as the beginning of nineteenth century, many cities were experimenting with legislated segregation (Fishback et al., 2022; Winling and Michney, 2021) with racial zoning laws in cities such as St. Louis and Baltimore. Prior to the New Deal, real estate lending was a profitable business but occurred across the color lines. Mortgages were shorter term, had higher interest rates with typical loan-to-value ratios of 50 percent. Following the New Deal legislations, the HOLC pegged the loan-to-value threshold at 80 percent while also creating the "residential security maps"

that speculated about neighborhood trends by specifically taking into account their racial and ethnic composition. Since mortgage loans in the redlined regions were not insured by the FHA, home in these already economically struggling urban areas had higher likelihood of defaults, which lead to reduced home ownership, home values, rents and higher vacancy rates Aaronson et al. (2021).

Black neighborhoods tended to be located in urban areas that were already economically struggling. As a result, almost all Black neighborhoods in the HOLC security maps were rated "hazardous" for mortgage lending and received a corresponding grade "D" and designated as red. Interestingly enough, not all "D"-rated neighborhoods were Black; however, all Black neighborhoods were marked red with only six known exceptions. One such inconsistent designation was in Savannah, Georgia with an "A"-rated or green designated Black neighborhood (Winling and Michney, 2021). According to the authors, although the HOLC never shared the security maps outside of government circles, they did disseminate the theories and methodologies behind the security maps with other organizations such as the Federal Home Loan Bank Board(FHLBB), who further passed on these information to private mortgage lenders.[6]

Urban areas which were predominantly Black and rated "hazardous" also faced a compounding problem of reduced access to credit and financial institutions, such as banks. This is because, the New Deal included provisions that encouraged the establishment of smaller community banks over larger banking conglomerates or national banks. The decision to advocate for small community banks over larger bank networks was not racially motivated but was implemented to protect small banks from both bank runs and competition of larger conglomerates. Nevertheless, these decisions negatively impacted the prospects for Black banks. Before the implementation of the New Deal, it was generally acknowledged that for Black banks to survive, they needed to be a branch of a larger national bank and cease

6. The HOLC and FHA continued educating real estate appraisers through local chapters of appraisal organizations, that adversely impacted Black home values simply because they tended to locate in redlined neighborhoods.

to be standalone banks. This is because, the Black community in general had insignificant amounts of stored wealth and limited access to credit, and hence could not develop within a system that tied all its deposits and loans only to those within its community borders (Baradaran, 2017).

Prominent Black entrepreneurs and socialites now faced the issue of providing consistent credit access in their local communities. However, providing credit access in these communities proved much harder since Black banks, in spite of increasing in numbers between 1918 and 1929, had their assets decreased sharply during the Great Depression; falling from $13,000,000 to $7,000,000 by the 1930s.[7] This is primarily because of less diversified loan portfolios. Their loans consisted of mostly real estate loans, which frequently fluctuated in value and very little commercial loans. "Inexperience of officers and employees", "expensiveness of many small accounts" and fraud on the part of the officers of the institutions (Harris, 1936; Mitchell, 1937) also exacerbated the insatiability of these institutions. Abram Harris suggested one of the ways Black banks could survive and serve their immediate communities was to become subsidiaries of other larger national banks. This would enable Black banks to access the mainstream banking network and utilize the national banks' large capital base. Such bank holding company ownership structure would have at least enabled credit constrained Black communities access to credit without risking future asset freezes and bank failures (Baradaran, 2017). However, once the banking legislations of the New Deal had passed, such arrangements were not possible and Black banks were left on their own to serve their communities and therefore "mirrored" the already narrowed Black "participation in American economic life" (Mitchell, 1937).

3 Data

I construct panel datasets by combining publicly available datasets: National Bureau of Economics Research's (NBER) Tract Distance Database to locate neighboring tracts within 1 mile and 5 miles of the census tracts under study, FDIC's Summary of Deposits (SoD),

7. This amounts to a fall from $248 million to $133 million in 2025.

HOLC's redlining scores and percentages within census tracts and the 5 year American Community Surveys (ACS), resulting in datasets of all census tracts with bank branches within counties where an MDI branch is present in the year 2011, a total of 12,953 tracts. All dollars values are converted to the 2021 dollar value using the Consumer Price Index (CPI) from US Bureau of Labor Statistics (2021) website.

3.1 Redlining Scores and Percentages

I collect redlining proportions for census tracts from two sources. Meier and Mitchell (2023), hosted on the Inter-university Consortium for Political and Social Research's (openICPSR) website and the University of Richmond's *Mapping Inequality* data containing the HOLC spatial data cross-walked into 2010 and 2020 census tracts. From the former dataset, I can obtain HOLC scores and from the latter, I recover percentages of redlined areas mapped into 2010 census tracts.

Meier and Mitchell (2023) classifies 12,834 urban census tracts representing 142 core-based statistical areas (CBSAs) across US based on the HOLC graded maps. They drop census tracts in which less than 20% of the land area was graded by HOLC. They then multiply HOLC graded percentages in each census tracts by number values 1-4, representing each HOLC grade. For example, if 50% of the census tract's graded area was classified "A" and 50% was "B," the census tracts receives a score of $((1 * 0.50) + (0.50 * 2)) = 1.50$. Lower historical redlining scores indicate higher grades, while higher scores up to 4.0 represent a greater portion of the area being considered hazardous and consequently having been redlined.

Using Meier and Mitchell (2023) I show that the median tract served by a Black MDI has a score of 2.00 whereas the neighboring tracts within a mile radius has an average score of 2.33. The 75 percentile tracts has a score of 3.38 whereas the neighboring tracts have a score of 3.23. Figure 1 through 4 show MDIs (primarily Black MDIs) and non-MDIs in four of the largest counties: Baltimore county, Cook county, Manhattan county and Bronx county.

3.2 Summary of Deposits

I obtain information on bank branches from the SoD published on the FDIC website. The SoDs contain information on every operating bank branch in the US, including street addresses, zip codes, geolocation data and individual branch deposits, published at the end of June of every year. Initially I collect a unique identification number for each institution assigned by the FDIC (CERT numbers) of MDIs from 2011 until 2021. Using the CERT numbers, I collect all counties where an MDI is present between the years 2011 and 2021. Then using those county codes I collect information on all other bank branches that are located within those counties from 2011 until 2021.

The SoD data does not contain the census tracts or census blocks where the branches are located so I use the "pygris" package in Python to geolocate latitude and longitude information of each branch to their corresponding census tracts based on the 2010 Census. Many branch locations have missing latitude and longitude data. In case of missing latitude and longitude information, I use the API from Google Maps to obtain latitude and longitude information from street addresses of each branch. Finally, I obtain the universe of all census tracts with bank branches in counties with an MDI in 2011, resulting in 12953 census tracts. For robustness checks, I construct two more sets of panels, spanning from 2011 until 2021. In these latter sets, I study all census tracts within counties with MDIs, consisting of 28,469 census tracts.

3.3 American Community Survey

Finally, I collect census tract characteristics from the 5-year ACS website, such as population, percentage of different racial communities, median household income, median home values etc. for all census tracts in counties with MDIs. Census tract characteristics are provided in Table 1.

3.4 Analysis of Summary Statistics

The four panels of Table 1 show MDIs tend to locate in tracts with higher proportions of the communities sharing their minority identity. Moreover, median household income generally fall between tracts primarily graded A and tracts primarily graded D. Additionally, percent of renters and vacancies increase between census tracts primarily graded A and those graded D, this is especially obvious for non-MDI tracts, Black MDI tracts and Asian MDI tracts. Even though I consider non-MDI tracts separately for the Summary Statistics table, many MDIs do locate within MDI tracts.

Black MDI tracts, as mentioned already, had a higher proportion of Black population across all graded tracts and even across tracts not graded. Notably, these tracts have higher vacancies and greater proportion of renters across all grades when compared with tracts with other kinds of MDIs and non-MDIs. At the same time, median household income decreased considerably between tracts graded A and those graded D while percentage of Supplemental Nutrition Assistance Program (SNAP) beneficiary households increased. Figure 1, Panel A through Panel D show median household income, percent of SNAP beneficiary households, percent of vacancies and percent of renters for different HOLC intervals and the four different sets of tracts. From the figure it is apparent that Black MDIs tracts with lower household income and consequently higher percent of SNAP beneficiary households, vacancies and renters tend to be disproportionately those with graded D or redlined.

4 Empirical analysis

I consider all census tracts within counties with bank branches for my primary analysis. I estimate four sets of equations, where the outcome variables are Black MDIs, Asian MDIs, Hispanic MDIs and non-MDIs. In the model I control for population within the census tract, population in all census tracts within a mile (or 5 miles), percent of the racial community sharing minority identity within the census tract and in all census tracts within a mile (or 5 miles), HOLC scores or the percentage of the tracts graded D, average HOLC scores or

graded D tracts within a mile radius (or 5 mile radius) and other bank branches.

I do not use income level variables such as median household income or per capita income as explanatory variables for three reasons. One, they vary widely and is dependent on the cost of living of different counties which is difficult to control for in the analysis. Two, as shown in Figure 5, panels 5a through 5d, lower median household income, higher percent of SNAP beneficiary households, higher rates of vacancies and higher rates of renters are strongly correlated with primary grade intervals of the census tracts. This means higher HOLC scores and relatively worse economic outcomes at the census tract level are strongly correlated. Three, in the primary analysis, I consider tracts that already have branches present, therefore, bank branching choices based on income characteristics of nearby communities are endogenous and already baked in. To account for income, mobility and general economic conditions of the tracts, I consider whether each census tract is designated to be low-or-moderate income (LMI), based on the 2010 Census and the percent of households within the tract with vehicles.

I estimate two models following Wang et al. (2024) where they introduce the Generalized Estimating Equations (GEEs) for estimating longitudinal data. Standard log-linearized models estimated using Ordinary Least Squares (OLS) and Generalized Linear Models (GLMs) can be quite misleading in the presence of heteroscedasticity. Therefore, they are not suitable for data with repeated observations because the former methods assume independence of observations. This independence of observations are violated in longitudinal settings where one observes within-unit correlations. GEEs are generally used to model population-averaged effects considering within-unit correlation. They are typically adopted to estimate the parameters of a generalized linear model when the correlation between repeated outcome observations are unknown (Liang and Zeger, 1986).

4.1 Estimation with HOLC scores:

$$\begin{aligned} f(y_{i,t}|x_{i,t},\beta_j) = exp(&\beta_1 Population \\ &+\beta_2 Population\ x\ mile + \beta_3 Percent\ sharing\ minority\ identity \\ &+\beta_4 Percent\ sharing\ minority\ identity\ x\ mile + \beta_5 HOLC\ score \\ &+\beta_6 HOLC\ score\ within\ x\ miles \\ &+\beta_7 LMI\ tract + \beta_8 Percent\ households\ w/\ vehicles \\ &+\beta_9 Other\ bank\ branches) + \nu_{i,t} \end{aligned} \tag{4.1}$$

4.2 Estimation with percent of the census tracts graded D:

$$\begin{aligned} f(y_{i,t}|x_{i,t},\beta_j) = exp(&\beta_1 Population \\ &+\beta_2 Population\ x\ mile + \beta_3 Percent\ sharing\ minority\ identity \\ &+\beta_4 Percent\ sharing\ minority\ identity\ x\ mile + \beta_5 Percent\ Graded\ D \\ &+\beta_6 Percent\ Graded\ D\ in\ census\ tracts\ within\ x\ miles \\ &+\beta_7 LMI\ tract + \beta_8 Percent\ households\ w/\ vehicles \\ &+\beta_7 Other\ bank\ branches) + \nu_{i,t} \end{aligned} \tag{4.2}$$

In essence, GEEs extend GLMs by introducing a working correlation matrix (e.g., exchangeable, autoregressive, unstructured) to model dependencies between repeated measurements and provide robust "sandwich" standard errors[8]. This paper assumes an exchangeable correlation structure, i.e., the correlation between any two measurements within the same unit of observations (census tracts) is time invariant, a reasonable assumption since I consider only eleven years of observations. An advantage of the GEE specification is as long as the mean function is correctly specified, parameter estimates from the GEE are consistent even if the working variance-covariance structure is misspecified (Wang et al., 2024), which is more generally difficult to pin down correctly.

8. "Sandwich" standard errors account for misspecification of the correlation structure

4.3 Robustness checks

To check for robustness, I construct two separate sets of panel data, spanning from 2011 until 2021. In these sets, I study all census tracts with or without bank branches within counties with MDIs, consisting of 28,469 census tracts. The construction mechanism follows similar methods used in the previous two datasets and results are overall similar. [9]. However, when in the latter case, Black MDI tracts are not anymore likely to be located within census tracts with higher HOLC scores or higher percentage of areas graded D when I consider census tract characteristics within 1 mile of the studied tracts. This likely arises because there is not much variation between HOLC scores (or percent of the tract areas graded D) within the individual census tracts and those located within a mile of the studied tracts in the larger sample. The results are provided in Appendix A.

5 Results

Estimates from the Poisson GEE model using HOLC scores as an explanatory variable are provided in Table 2 through Table 4. In Table 2, neighboring tracts are those within 1 miles of the studied tracts whereas in Table 4, neighboring tracts are those within 5 miles of the studied tracts.

5.1 Results using HOLC or redlining scores by Meier and Mitchell (2023)

Table 2 and Table 4 show estimates from the Poisson GEE model using the HOLC or redlining score variable. At first glance, holding all other control variables constant, Black MDIs are 18-28 percent less likely to locate in census tracts for each 1000 increase in their population. Similarly, Asian MDIs are 5 percent less likely to locate in census tracts for each 1000 increase in their population. Whereas non-MDIs are 4 percent more likely to locate in census tracts for each 1000 increase in their population. It is evident form Figure **??** that Black MDIs were located in census tracts that generally had higher vacancy rates. All three types of MDIs, Black MDIs, Asian MDIs and Hispanic MDIs are more likely to locate in

9. The latter results are provided in Appendix A

census tracts with a higher percentage of Blacks, Hispanics and Asians respectively at the census tract level and within 1 mile of the studied tracts.

Moreover, Black MDIs are 9 percent more likely to locate in census tracts for each one point increase in their HOLC scores. In other words, holding all other control variable constant, including the number of non-MDIs branches, Black MDIs are more likely to locate in census tracts with higher scores. Similarly, non-MDI bank branches are 10 percent less likely to locate in tracts for each one point increase in their HOLC scores. The results hold when I consider neighboring tracts within both 1 mile and 5 miles of the studied tracts. Asian and Hispanic MDIs do not locate in census tracts with higher HOLC scores, although Black MDIs and non-MDIs do tend to locate close census tracts with higher HOLC scores. Therefore, Black MDIs are 18-30 percent more likely to locate in tracts for each one point increase in the average HOLC scores of their neighboring tracts and non-MDIs are 11-16 percent more likely to locate in tracts for each one point increase in the average HOLC scores of their neighboring tracts. Hispanic MDIs on the other hand are 24-50 percent less likely to locate in tracts for each one point increase in the average HOLC scores of their neighboring tracts.

5.2 Results using percentage of census tract area redlined or graded D:

Table 3 and Table 5 show estimates from the Poisson GEE model using percent of census tracts graded D as an explanatory variable. In Table 3, neighboring tracts are those within 1 miles of the studied tracts whereas in Table 5, neighboring tracts are those within 5 miles of the studied tracts. The results are largely similar to Table 2 and Table 4 for population and other bank branches. Again, all three types of MDIs, Black MDIs, Asian MDIs and Hispanic MDIs are more likely to locate in census tracts with a higher percentage of Blacks, Hispanics and Asians respectively at the census tract level and within 5 mile of the studied tracts.

Finally, Black MDIs are 4-8 percent more likely to locate in tracts for each ten percentage point increase in tract area with Grade D. In other words, holding all other control variable

constant, including the number of non-MDIs branches, Black MDIs are more likely to locate in census tracts with more redlining. While non-MDIs bank branches are 4-5 percent less likely to locate in tracts for each ten percentage point increase in tract area with Grade D. At the same time, Black MDIs are 13-19 percent more likely to locate in tracts for each ten percentage point increase in graded D areas within their neighboring tracts, while non-MDIs are 7-9 percent more likely to locate in tracts for each ten percentage points increase in graded D areas within their neighboring tracts

My results show a degree of spatial clustering among Black MDIs, Asian MDIs, Hispanic MDIs and non-MDI bank branches, as is apparent from Figure 1 through 4. The figures show MDI and non-MDI branch presence in four of the largest counties with Black MDIs, such as Cook county, Baltimore county, Manhattan county and Bronx county. The HOLC maps contained contiguous regions of the highest grade (Green with Grade A) and the lowest grade (Red with Grade D), and hence the result that non-MDI bank branches tend to locate within a mile or 5 miles of the lowest graded neighborhoods is unsurprising.

I also show that Black MDIs and Asian MDIs are at least 80 percent more likely to locate in census tracts that are designated as LMI, holding all other explanatory variables constant. The results are consistent across all different kinds of specifications. Moreover, Black MDIs are 10 percent more likely to locate in census tracts for each 10 percent decrease in the percentage of households with vehicles. The latter result only holds when I consider tracts within 1 mile radius and disappears when I start considering tracts within 5 mile radius of the studied tracts.

6 Conclusion

This paper studies the location choices of depository institutions, known as Minority Depository Institutions (MDIs) and whether these institutions have a higher likelihood of locating in neighborhoods with lower HOLC grades when compared to non-MDIs. In my primary analysis, I study all census tracts with bank branches within counties with MDIs. I construct two sets of data, one with features of all neighboring tracts within a mile of the

census tracts under study and one with features of all neighboring tracts within 5 miles of the census tracts under study. As robustness checks, I construct two larger panels, spanning from 2011 until 2021. In these latter sets, where I study all census tracts within counties with MDIs, consisting of 28,469 census tracts.

I use Black MDIs, Asian MDIs, Hispanic MDIs and non-MDIs within census tracts as the outcomes variables. I control for population variables, percent of the racial community sharing minority identity with the MDIs as supporting explanatory variables. My primary explanatory variables are HOLC scores and percentage of census tract areas graded D. I also control for average HOLC scores and percent of graded D or redlined areas in neighboring tracts within 1 mile and 5 miles respectively. I estimate the models utilizing Poisson Generalized Estimating Equations (GEEs).

Results show Black MDIs are 9 percent more likely to locate in census tracts for each one point increase in their HOLC scores. Similarly, non-MDI bank branches are 10 percent less likely to locate in tracts for each one point increase in their HOLC scores. The results hold when I consider neighboring tracts within both 1 mile and 5 miles of the studied tracts. Asian and Hispanic MDIs do not locate in census tracts with higher HOLC scores, although Black MDIs and non-MDIs do tend to locate close census tracts with higher HOLC scores. Conversely, Hispanic MDIs are 25-50 percent less likely to locate in tracts for each one point increase in the average HOLC scores of their neighboring tracts.

The primary contribution of the paper is to connect historical practices of color coding urban neighborhoods with the present day location choices of Black owned banks. In the paper, I demonstrate a positive relation between previously redlined urban neighborhoods and the prevalence of Black banks within these neighborhoods when compared with other kinds of depository institutions or banks. To provide a mechanism for the observed phenomenon, I draw on historical literature focusing on the interaction between the HOLC maps, the residents of the redlined neighborhoods, their lack of access to credit and how the need for this access lead to the formation of Black banks within these neighborhoods.

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Table 1: Summary Statistics: Population variables and median household income are in thousands.

	Panel A: Black MDI tracts				
	Not Graded	Grade A	Grade B	Grade C	Grade D
Count	70	4	11	24	40
Black MDIs	1.07	1.25	1.00	1.00	1.025
	(0.26)	(0.50)	(0.000)	(0.000)	(0.000)
Non MDIs	3.81	1.00	0.55	1.21	2.32
	(8.73)	(2.00)	(0.688)	(1.41)	(4.51)
LMI tract	0.54	0.75	0.72	0.75	0.85
	(0.50)	(0.50)	(0.46)	(0.44)	(0.36)
Population (000s)	3.99	3.98	3.79	3.51	2.28
	(1.89)	(1.33)	(1.75)	(2.54)	(0.79)
Population (000s)1 mile	11.77	23.54	49.12	29.72	46523
	(17.72)	(2.18)	(59.51)	(26.96)	(58.49)
Population (000s) 5 miles	300.40	807.01	824.84	658.29	738.18
	(275.40)	(387.59)	(893.61)	(526.56)	(818.15)
Percent Black	63.41	63.25	75.91	71.45	69.73
	(29.17)	(41.32)	(31.57)	(30.44)	(23.75)
Percent Black 1 mile	41.17	56.25	77.36	64.50	67.50
	(36.91)	(32.54)	(23.16)	(31.54)	(18.97)
Percent Black 5 miles	51.67	28.75	58.91	49.83	48.78
	(23.80)	(17.88)	(16.17)	(23.24)	(16.04)
Percent Asian	3.54	8.25	3.81	3.63	3.60
	(5.26)	(11.41)	(2.36)	(3.81)	(4.77)
Percent Hispanic	10.14	5.00	4.64	16.70	7.90
	(13.90)	(1.41)	(7.07)	(23.20)	(11.01)
Percent White	26.18	37.00	18.27	16.29	21.25
	(24.47)	(26.15)	(30.47)	(19.30)	(19.75)
HOLC Score	0.00	1.33	2.08	3.01	3.88
	(0.00)	(0.36)	(0.15)	(0.14)	(0.23)
Average Neighbor Score 1 mile	0.44	1.82	2.35	2.79	3.48
	(0.92)	(0.34)	(0.48)	(0.80)	(0.47)
Average Neighbor Score 5 miles	0.85	2.25	2.37	2.45	2.53
	(1.04)	(0.71)	(0.67)	(0.64)	(0.63)
Percent Graded D	0.27	0.00	1.83	5.26	74.32
	(1.20)	(0.00)	(6.06)	(8.85)	(28.81)
Average Graded D 1 mile	4.76	5.34	7.74	20.39	60.99
	(13.12)	(10.65)	(8.56)	(17.55)	(22.93)
Average Grade D 5 miles	8.46	17.23	19.95	21.83	28.48
	(12.85)	(7.13)	(12.55)	(12.11)	(11.43)
Median Household Income (000s)	53.56	79.98	50.50	43.02	37.44
	(27.30)	(47.11)	(9.92)	(18.07)	(20.35)
Percent Households on SNAP	18.24	8.85	17.95	23.80	28.36
	(11.27)	(5.94)	(11.34)	(13.48)	(12.83)
Percent Vacancies	14.19	13.37	12.67	18.34	21.01
	(7.45)	(7.64)	(7.62)	(11.75)	(8.79)
Percent Renters	49.81	50.53	60.10	61.21	73.01
	(20.76)	(28.27)	(29.80)	(22.46)	(15.81)

Table 1: Summary Statistics: Population variables and median household income are in thousands.

	Panel B: Asian MDI tracts				
	Not Graded	Grade A	Grade B	Grade C	Grade D
Count	280	8	26	60	36
Asian MDIs	1.53	1.50	1.23	1.67	2.05
	(1.16)	(0.76)	(0.51)	(1.26)	(1.80)
Non MDIs	3.24	3.00	2.38	2.33	3.28
	(5.46)	(0.92)	(4.00)	(3.60)	(4.47)
LMI tract	0.32	0.13	0.46	0.63	0.75
	(0.47)	(0.35)	(0.51)	(0.49)	(0.44)
Population (000s)	4.718	5.472	4.636	4.515	4.873
	(1.957)	(1.001)	(1.350)	(1.400)	(2.584)
Population (000s) 1 mile	16.550	11.881	47.693	57.340	73.837
	(29.259)	(8.314)	(26.088)	(47.973)	(54.931)
Population (000s) 5 miles	381.670	712.560	874.435	896.224	1297.213
	(345.338)	(216.809)	(441.573)	(502.675)	(682.557)
Percent Asian	28.0	35.25	36.08	43.68	42.72
	(22.70)	(21.49)	(221.18)	(22.49)	(26.10)
Percent Asian 1 mile	20.59	24.37	30.04	37.23	27.67
	(20.24)	(23.99)	(19.56)	(19.26)	(13.85)
Percent Asian 5 miles	18.90	21.88	18.50	22.47	14.75
	(13.16)	(13.09)	(9.67)	(11.50)	(7.07)
Percent Black	7.09	8.37	5.81	6.08	12.22
	(9.18)	(11.61)	(8.58)	(11.57)	(18.47)
Percent Hispanic	23.56	9.25	18.96	25.88	20.58
	(21.25)	(9.30)	(16.59)	(20.17)	(19.38)
Percent White	50.95	51.75	45.38	35.35	33.97
	(22.57)	(21.93)	(23.91)	(19.22)	(19.35)
HOLC Score	0.00	1.31	2.17	2.95	3.86
	(0.00)	(0.25)	(0.19)	(0.14)	(0.26)
Average Neighbor Score 1 mile	0.25	1.60	2.43	2.71	2.84
	(0.68)	(0.83)	(0.45)	(0.43)	(0.83)
Average Neighbor Score 5 miles	0.44	2.46	2.42	2.38	2.71
	(0.83)	(0.20)	(0.54)	(0.54)	(0.67)
Percent Graded D	0.18	0.80	0.50	1.72	60.59
	(1.19)	(2.25)	(1.66)	(6.08)	(28.52)
Average Graded D 1 mile	2.89	0.63	4.70	8.02	41.19
	(9.31)	(1.77)	(8.57)	(11.16)	(22.91)
Average Grade D 5 miles	4.03	10.38	16.00	15.20	31.50
	(9.72)	(8.92)	(7.41)	(9.90)	(14.02)
Median Household Income (000s)	84.18	135.51	80.56	62.66	53.71
	(39.56)	(41.52)	(28.06)	(21.58)	(34.05)
Percent Households on SNAP	7.25	4.21	5.26	7.04	13.86
	(6.93)	(2.09)	(4.09)	(7.05)	(14.41)
Percent Vacancies	8.73	4.76	7.35	7.44	10.31
	(6.82)	(1.38)	(3.70)	(4.94)	(9.81)
Percent Renters	44.22	22.56	60.12	65.37	74.60
	(24.76)	(15.57)	(18.84)	(21.66)	(21.79)

Table 1: Summary Statistics: Population variables and median household income are in thousands.

	Panel C: Hispanic MDI tracts				
	Not Graded	Grade A	Grade B	Grade C	Grade D
Count	389	6	18	38	36
Hispanic MDIs	1.21	1.33	1.27	1.18	1.19
	(0.63)	(0.82)	(0.75)	(0.51)	(0.1.17)
Non MDIs	2.62	5.33	5.00	2.74	2.69
	(3.43)	(6.86)	(6.86)	(4.90)	(4.68)
LMI tract	0.36	0.33	0.56	0.79	0.72
	(0.48)	(0.52)	(0.51)	(0.41)	(0.45)
Population (000s)	5.299	4.705	5.346	4.457	4.681
	(2.925)	(1.629)	(2.334)	(2.235)	(2.164)
Population (000s) 1 mile	6.324	28.894	77.354	74.269	86.981
	(10.434)	(36.415)	(81.465)	(61.393)	(61.822)
Population (000s) 5 miles	197.214	642.007	1185.792	1212.228	1463.552
	(214.331)	(670.789)	(950.083)	(860.709)	(940.940)
Percent Hispanic	51.23	49.33	49.17	58.13	53.72
	(32.77)	(26.64)	(28.23)	(29.50)	(33.65)
Percent Hispanic 1 mile	27.04	53.00	45.22	51.00	49.61
	(35.47)	(23.38)	(29.56)	(25.13)	(30.53)
Percent Hispanic 5 miles	47.71	56.33	49.89	43.74	39.56
	(32.67)	(19.73)	(19.31)	(19.97)	(19.46)
Percent Asian	3.86	3.83	7.50	9.39	7.47
	(7.28)	(4.67)	(11.98)	(14.02)	(8.48)
Percent Black	6.61	6.50	10.61	9.82	16.69
	(11.33	(6.32)	(16.68)	(14.00)	(21.89)
Percent White	77.48	75.50	59.61	54.24	53.39
	(15.98)	(18.67)	(27.53)	(26.17)	(27.60)
HOLC Score	0.00	1.19	2.12	2.99	3.85
	(0.00)	(0.25)	(0.20)	(0.12)	(0.25)
Average Neighbor Score 1 mile	0.10	1.45	2.01	2.64	3.13
	(0.46)	(0.63)	(0.93)	(0.64)	(0.59)
Average Neighbor Score 5 miles	0.20	1.83	2.04	2.50	2.55
	(0.51)	(0.68)	(0.83)	(0.60)	(0.63)
Percent Graded D	0.10	0.00	0.02	2.98	65.36
	(1.07)	(0.00)	(0.09)	(5.85)	(32.90)
Average Graded D 1 mile	0.70	0.40	14.15	11.71	47.76
	(4.27)	(0.73)	(17.11)	(15.44)	(25.40)
Average Grade D 5 miles	1.43	12.99	19.27	21.38	27.56
	(4.44)	(7.57)	(11.87)	(12.26)	(11.63)
Median Household Income	64.05	67.20	64.45	52.74	54.69
	(33.19)	(27.59)	(29.16)	(21.36)	(28.29)
Percent Households on SNAP	15.35	13.60	15.64	17.28	20.22
	(12.41)	(12.75)	(14.15)	(11.20)	(13.95)
Percent Vacancies	12.93	19.45	12.82	13.89	10.10
	(9.64)	(10.81)	(9.13)	(13.18)	(5.48)
Percent Renters	40.06	59.75	63.60	68.28	74.18
	(21.74)	(28.50)	(21.85)	(20.88)	(15.57)

Table 1: Summary Statistics: Population variables and median household income are in thousands.

	Panel D: Non-MDI tracts				
	Not Graded	Grade A	Grade B	Grade C	Grade D
Count	8898	230	622	1244	872
MDIs	0.00	0.00	0.00	0.00	0.00
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Non MDIs	2.40	2.80	2.34	2.09	20.04
	(2.07)	(2.82)	(2.04)	(1.78)	(2.04)
LMI tract	0.23	0.07	0.30	0.48	0.61
	(0.42)	(0.25)	(0.46)	(0.50)	(0.49)
Population (000s)	4.734	3.971	4.335	4.172	3.825
	(2.222)	(1.477)	(1.722)	(1.750)	(2.007)
Population (000s) 1 mile	7.643	26.271	36.609	40.905	48.888
	(13.994)	(48.438)	(44.427)	(41.647)	(50.899)
Population (000s) 5 miles	230.804	563.010	692.048	768.315	899.946
	(236.150)	(640.945)	(610.850)	(611.357)	(791.359)
Percent Asian	7.80	5.38	7.89	9.25	8.12
	(10.52)	(7.04)	(9.88)	(11.28)	(10.28)
Percent Black	12.08	11.57	17.68	17.61	23.04
	(18.01)	(18.61)	(26.16)	(25.30)	(28.23)
Percent Hispanic	19.16	9.17	15.43	24.49	26.40
	(20.94)	(13.50)	(20.22)	(25.78)	(26.51)
Percent White	68.74	79.80	66.41	60.42	55.09
	(22.92)	(20.20)	(26.71)	(26.53)	(26.82)
Percent White 1 mile	40.02	66.12	59.38	56.64	62.95
	(36.63)	(28.94)	(26.84)	(25.26)	(23.47)
Percent White 5 miles	64.43	58.24	55.28	54.10	51.24
	(21.01)	(15.17)	(16.13)	(15.31)	(14.58)
HOLC Score	0.00	1.31	2.12	2.94	3.82
	(0.00)	(0.25)	(0.18)	(0.15)	(0.24)
Average Neighbor Score 1 mile	0.12	1.66	2.05	2.58	3.00
	(0.52)	(0.85)	(0.78)	(0.79)	(0.92)
Average Neighbor Score 5 miles	0.30	1.87	2.12	2.30	2.50
	(0.62)	(0.66)	(0.63)	(0.66)	(0.66)
Percent Graded D	0.14	0.45	0.88	2.87	62.54
	(1.31)	(2.21)	(3.25)	(7.53)	(28.54)
Average Graded D 1 mile	0.95	5.89	6.29	11.40	42.76
	(6.22)	(13.13)	(11.34)	(15.58)	(25.17)
Average Grade D 5 miles	2.17	14.30	15.16	17.34	26.88
	(6.37)	(11.03)	(10.44)	(10.92)	(13.17)
Median Household Income (000s)	83.75	129.32	85.48	68.67	60.95
	(40.33)	(59.75)	(41.46)	(30.06)	(32.05)
Percent Households on SNAP	7.78	5.40	8.85	12.08	18.81
	(7.78)	(5.35)	(9.25)	(11.41)	(13.65)
Percent Vacancies	9.64	10.78	9.38	9.97	13.32
	(7.85)	(8.66)	(7.08)	(7.02)	(8.62)
Percent Renters	35.38	30.33	45.06	54.36	63.11
	(23.59)	(19.61)	(23.73)	(22.83)	(20.19)

Table 2: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on HOLC Score using Meier and Mitchell (2023)				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
(Intercept)	-4.849^{***}	-4.482^{***}	-4.388^{***}	0.121^{*}
	(0.321)	(0.292)	(0.312)	(0.061)
Population (000s)	-0.182^{***}	-0.047^{***}	-0.007	0.032^{***}
	(0.020)	(0.012)	(0.007)	(0.001)
Population (000s) 1 mile	0.003^{***}	0.003^{***}	0.007^{***}	0.001^{***}
	(0.001)	(0.001)	(0.001)	(0.000)
HOLC score	0.087^{**}	-0.051	-0.044	-0.093^{***}
	(0.041)	(0.031)	(0.028)	(0.008)
Ave HOLC score 1 mile	0.169^{***}	0.105^{***}	-0.279^{***}	0.111^{***}
	(0.047)	(0.030)	(0.040)	(0.008)
LMI tract	0.472^{***}	0.626^{***}	0.114^{*}	-0.007
	(0.074)	(0.047)	(0.061)	(0.009)
Percent household w/ vehicles	-0.098^{**}	0.037	0.021	0.030^{***}
	(0.033)	(0.030)	(0.031)	(0.006)
Other banks' branches	0.096^{***}	0.065^{***}	0.092^{***}	
	(0.005)	(0.004)	(0.004)	
Percent Black	0.137^{***}			-0.029^{***}
	(0.010)			(0.002)
Percent Blacks 1 mile	0.019^{***}			
	(0.001)			
Percent Asians		0.149^{***}		0.027^{***}
		(0.016)		(0.002)
Percent Asians 1 mile		0.033^{***}		
		(0.002)		
Percent Hispanic			0.123^{***}	-0.063^{***}
			(0.008)	(0.001)
Percent Hispanics 1 mile			0.008^{***}	
			(0.001)	
Percent White				0.027^{***}
				(0.001)
MDI branches				0.228^{***}
				(0.010)
Scale	0.767	1.306	0.914	2.488
Observations	140990	140990	140990	140990

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 3: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on percent graded D within census tracts				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
Intercept)	-4.844^{***}	-4.401^{***}	-4.457^{***}	0.111
	(0.321)	(0.291)	(0.313)	(0.066)
Population (000s)	-0.174^{***}	-0.051^{***}	0.002	0.031^{***}
	(0.022)	(0.013)	(0.007)	(0.001)
Population (000s) 1 mile	0.003^{***}	0.004^{***}	0.003^{***}	0.001^{***}
	(0.001)	(0.000)	(0.001)	(0.000)
Percent Graded D	0.045^{**}	0.011	-0.002	-0.050^{***}
	(0.016)	(0.014)	(0.011)	(0.003)
Ave Graded D 1 mile	0.123^{***}	-0.003	-0.074^{***}	0.066^{***}
	(0.022)	(0.018)	(0.014)	(0.004)
LMI tracts	0.481^{***}	0.636^{***}	0.087	-0.006
	(0.076)	(0.045)	(0.064)	(0.010)
Percent household w/ vehicles	-0.088^{**}	0.034	0.018	0.028^{***}
	(0.033)	(0.030)	(0.031)	(0.006)
Other banks' branches	0.093^{***}	0.065^{***}	0.091^{***}	
	(0.005)	(0.003)	(0.004)	
Percent Black	0.129^{***}			-0.026^{***}
	(0.011)			(0.005)
Percent Black 1 mile	0.020^{***}			
	(0.001)			
Percent Asian		0.149^{***}		0.028^{***}
		(0.016)		(0.002)
Percent Asian 1 mile		0.033^{***}		
		(0.002)		
Percent Hispanic			0.118^{***}	-0.063^{***}
			(0.009)	(0.002)
Percent Hispanic 1 mile			0.008^{***}	
			(0.001)	
Percent White				0.030^{***}
				(0.003)
MDI branches				0.248^{***}
				(0.011)
Scale	0.736	1.292	0.945	2.486
Observations	140990	140990	140990	140990

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 4: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on HOLC Score using Meier and Mitchell (2023)				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
(Intercept)	-5.302^{***}	-5.192^{***}	-4.753^{***}	-0.022
	(0.330)	(0.279)	(0.304)	(0.061)
Population (000s)	-0.294^{***}	-0.040^{***}	-0.026^{**}	0.034^{***}
	(0.022)	(0.012)	(0.008)	(0.001)
Population (000s) 5 miles	0.000^{*}	0.000^{***}	0.001^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
HOLC score	0.087^{**}	-0.036	0.036	-0.102^{***}
	(0.034)	(0.029)	(0.021)	(0.006)
Ave HOLC score 5 miles	0.268^{***}	0.078	-0.434^{***}	0.158^{***}
	(0.055)	(0.043)	(0.034)	(0.008)
LMI tract	0.806^{***}	0.788^{***}	0.100^{*}	-0.001
	(0.076)	(0.045)	(0.044)	(0.009)
Percent household w/ vehicles	-0.023	0.062^{*}	0.012	0.039^{***}
	(0.033)	(0.028)	(0.031)	(0.006)
Other banks' branches	0.084^{***}	0.075^{***}	0.105^{***}	
	(0.005)	(0.003)	(0.003)	
Percent Black	0.132^{***}			-0.031^{***}
	(0.010)			(0.002)
Percent Black 5 miles	0.015^{***}			
	(0.002)			
Percent Asian		0.145^{***}		0.022^{***}
		(0.014)		(0.002)
Percent Asian 5 miles		0.046^{***}		
		(0.002)		
Percent Hispanic			0.061^{***}	-0.062^{***}
			(0.007)	(0.001)
Percent Hispanic 5 miles			0.023^{***}	
			(0.001)	
Percent White				0.027^{***}
				(0.001)
MDI branches				0.225^{***}
				(0.010)
Scale	0.663	1.164	0.887	2.459
Observations	140990	140990	140990	140990

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 5: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on percent graded D within census tracts				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
(Intercept)	-5.192^{***}	-5.095^{***}	-4.879^{***}	0.059
	(0.328)	(0.276)	(0.299)	(0.061)
Population (000s)	-0.294^{***}	-0.045^{***}	-0.021^{**}	0.032^{***}
	(0.021)	(0.012)	(0.008)	(0.001)
Population (000s) 5 miles	0.000^{**}	0.001^{***}	0.001^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Percent Graded D	0.079^{***}	-0.011	0.028^{**}	-0.035^{***}
	(0.011)	(0.011)	(0.010)	(0.002)
Ave Graded D 5 miles	0.170^{***}	-0.063	-0.333^{***}	0.089^{***}
	(0.032)	(0.033)	(0.024)	(0.006)
LMI tract	0.813^{***}	0.810^{***}	0.072	-0.014
	(0.077)	(0.044)	(0.044)	(0.009)
Percent household w/ vehicles	-0.018	0.057^{*}	0.014	0.033^{***}
	(0.033)	(0.028)	(0.030)	(0.006)
Other banks' branches	0.083^{***}	0.080^{***}	0.107^{***}	
	(0.005)	(0.003)	(0.003)	
Percent Black	0.130^{***}			-0.030^{***}
	(0.010)			(0.002)
Percent Black 5 miles	0.015^{***}			
	(0.002)			
Percent Asian		0.149^{***}		0.025^{***}
		(0.013)		(0.002)
Percent Asians 5 miles		0.044^{***}		
		(0.002)		
Percent Hispanic			0.060^{***}	-0.062^{***}
			(0.006)	(0.001)
Percent Hispanic 5 miles			0.023^{***}	
			(0.001)	
Percent White				0.027^{***}
				(0.001)
MDIs branches				0.228^{***}
				(0.010)
Scale	0.669	1.148	0.908	2.481
Observations	140990	140990	140990	140990

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

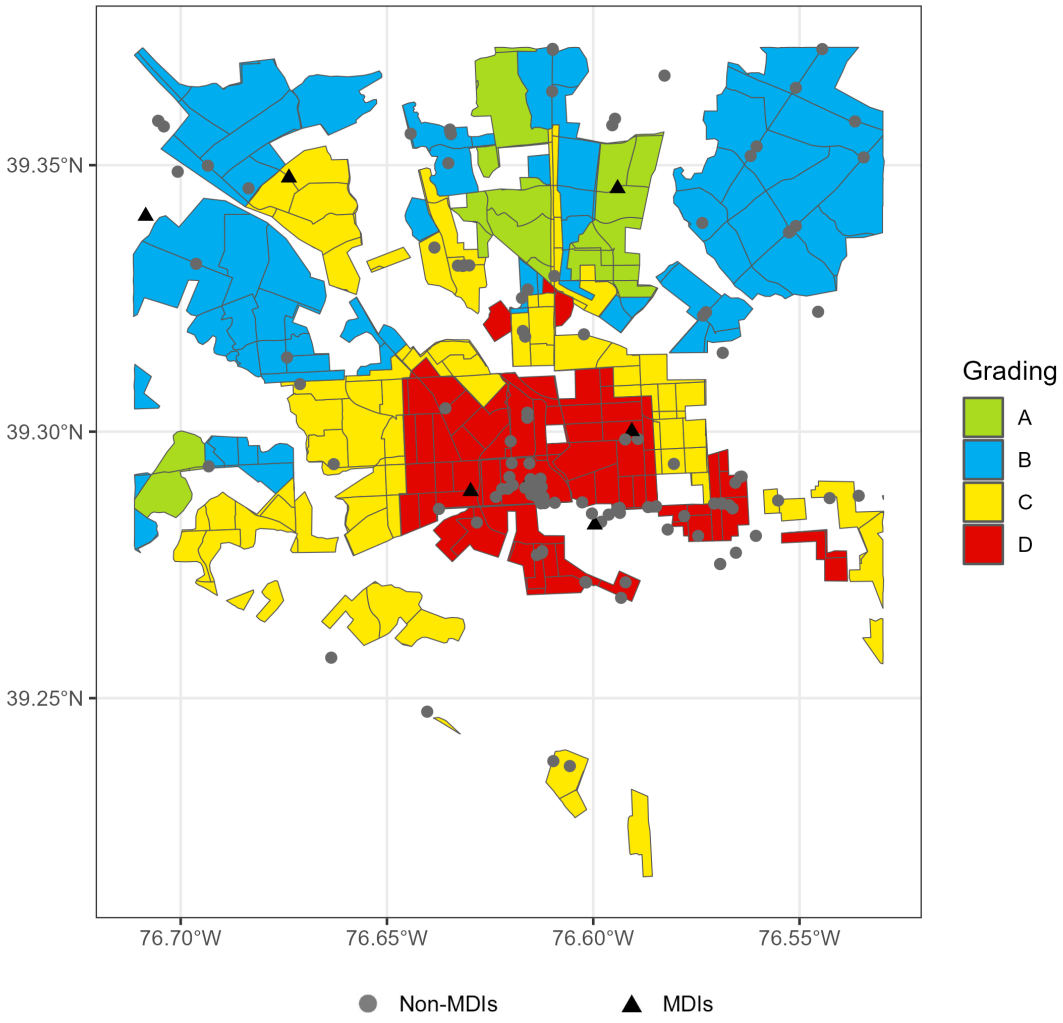


Figure 1: MDI and non-MDI branches in Baltimore county in 2011.

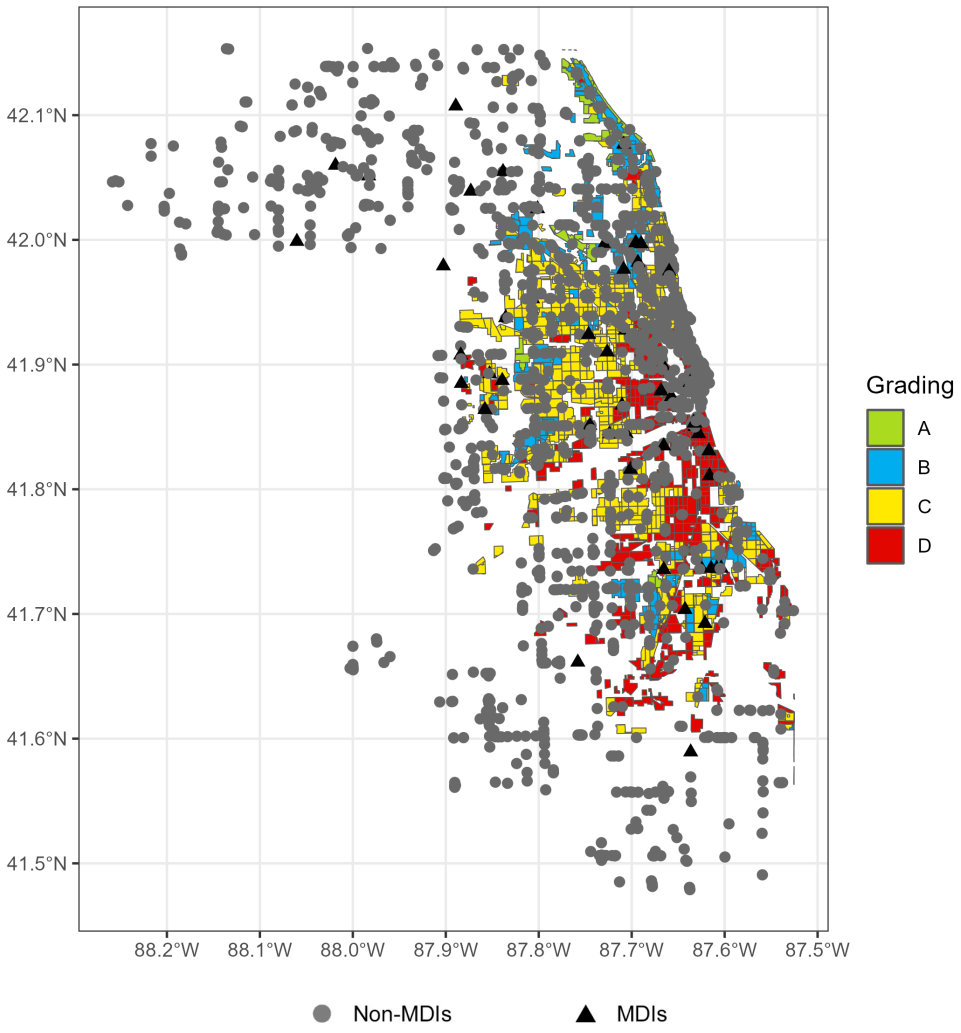


Figure 2: MDI and non-MDI branches in Cook county in 2011.

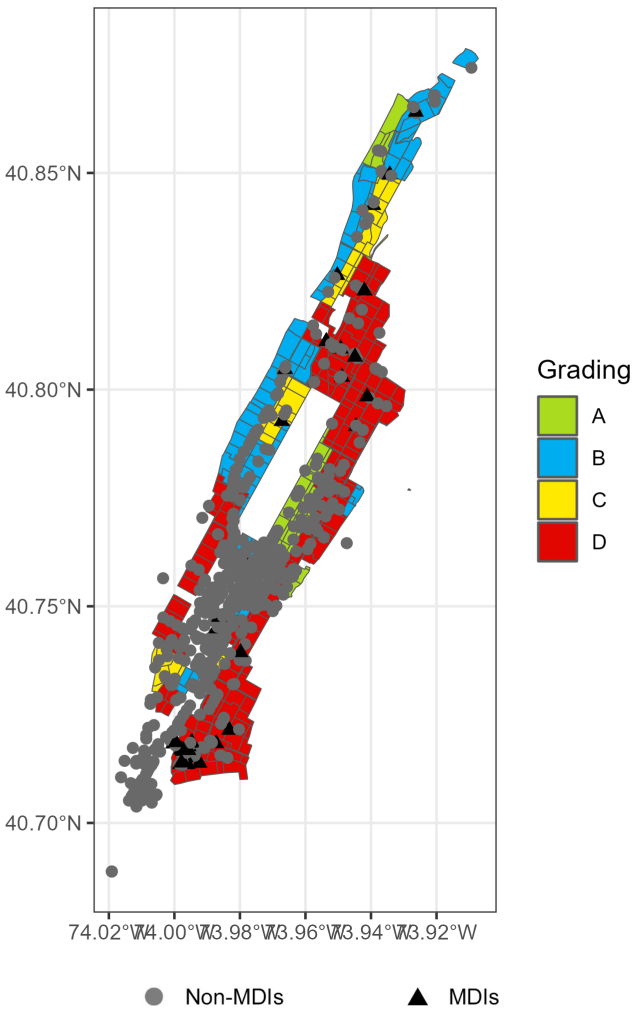


Figure 3: MDI and non-MDI branches in Manhattan county in 2011.

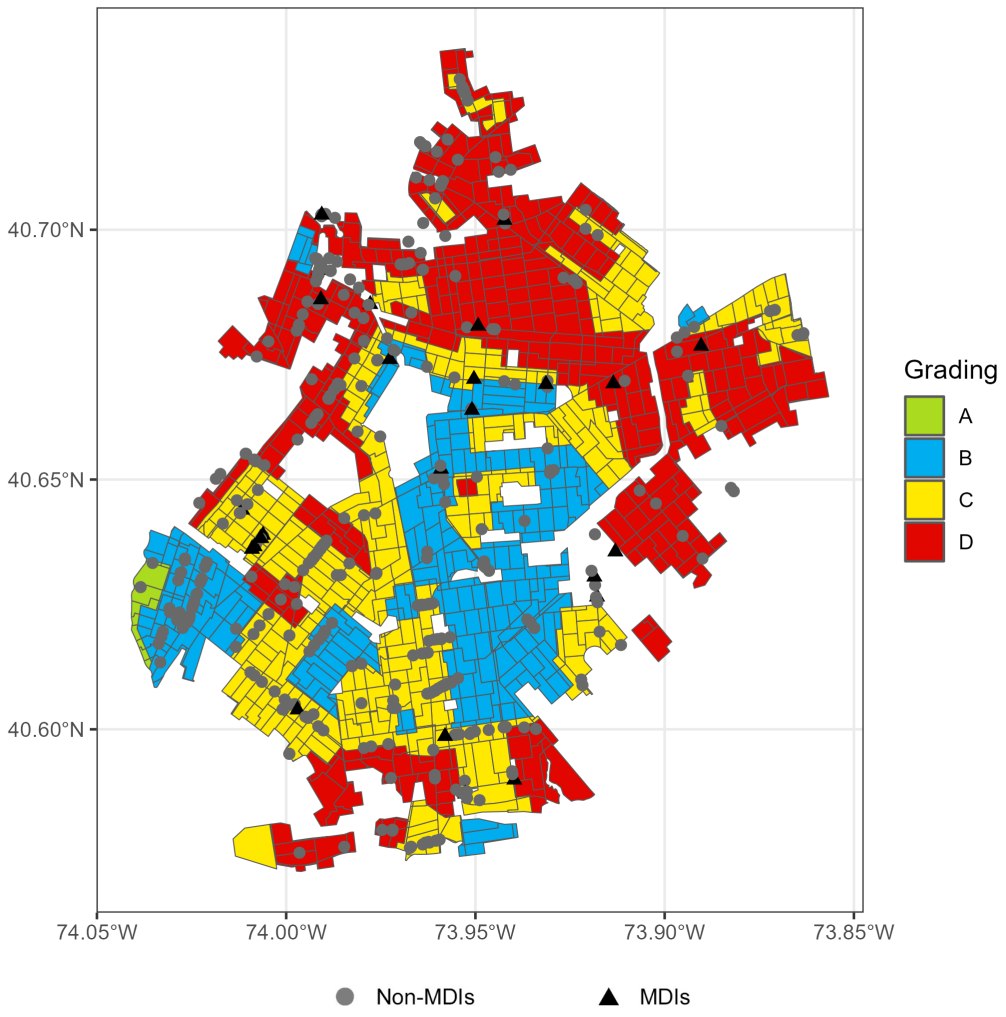
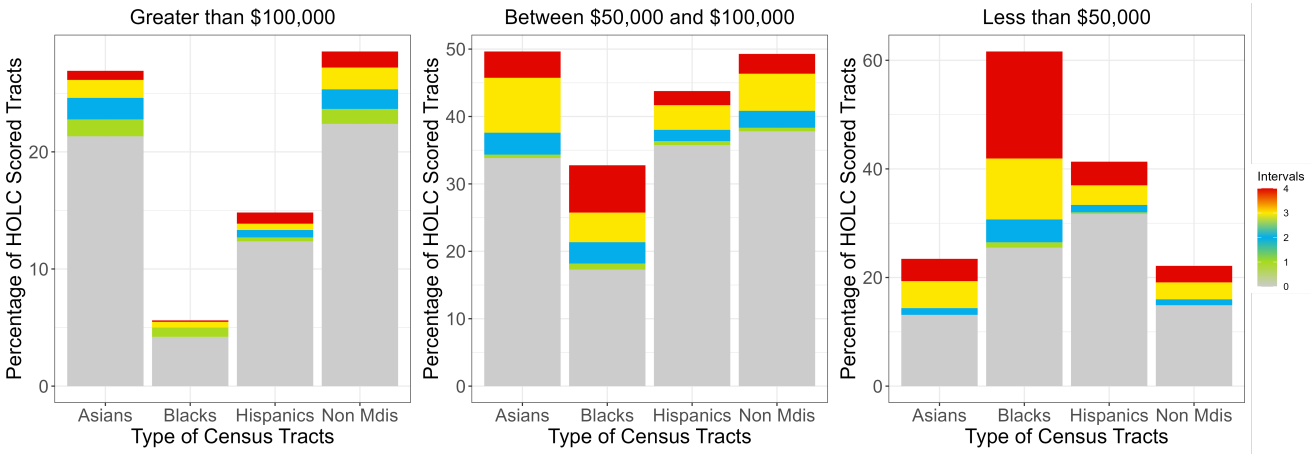
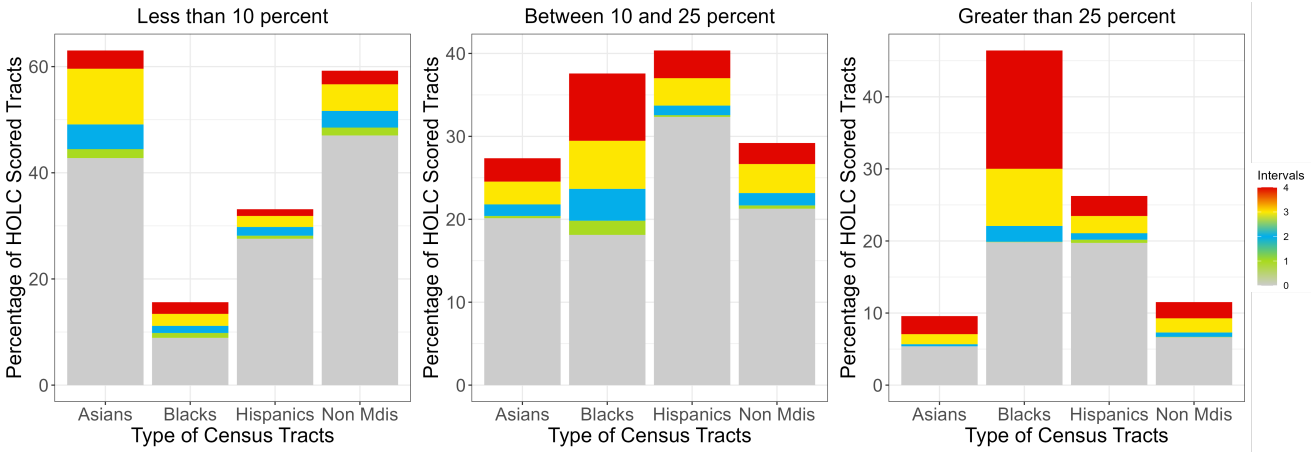


Figure 4: MDI and non-MDI branches in Bronx county in 2011.

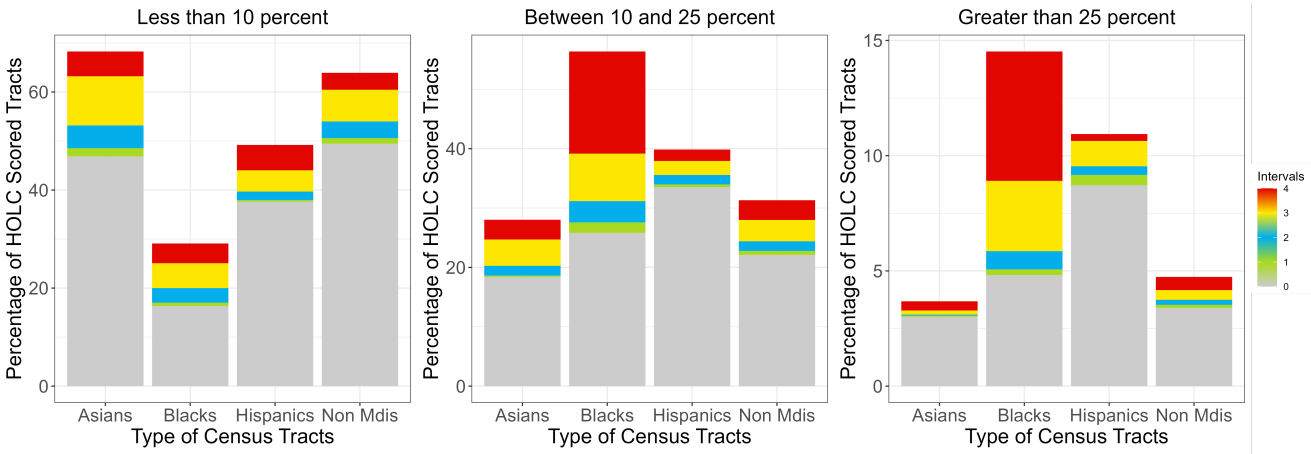


Panel A - Median household income.

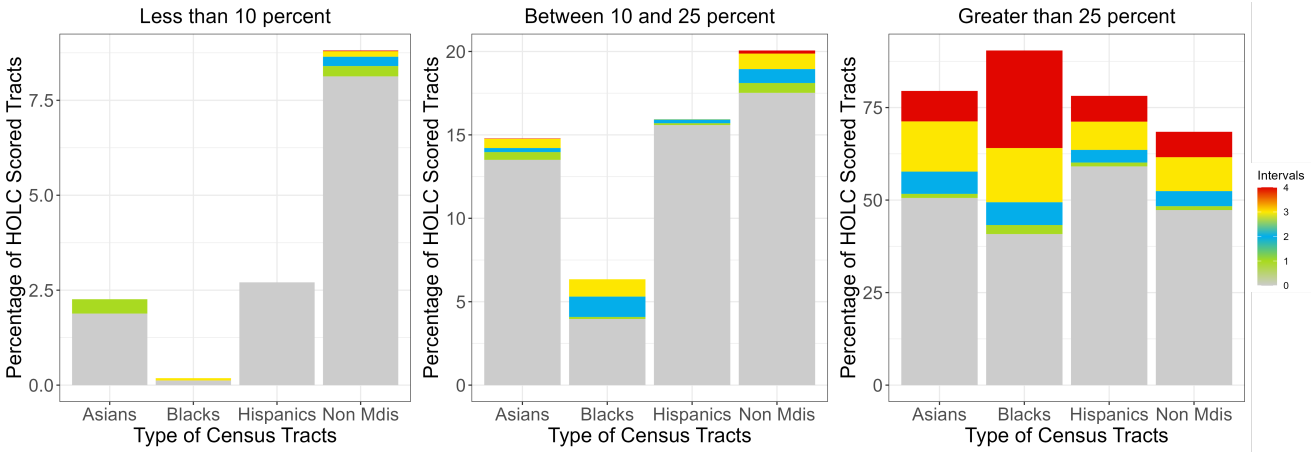


Panel B - Percent of households with SNAP.

Figure 5: Distribution of census tracts by MDI types and percentage of HOLC scored tracts



Panel C - Percent of vacancies.



Panel D - Percent of renters.

Figure 5: Distribution of census tracts by MDI types and percentage of HOLC scored tracts

A Appendix: Estimation using all census tracts in counties with MDIs

Stuff stuff stuff

Table A1: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on HOLC Score using Meier and Mitchell (2023)				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
(Intercept)	-6.669^{***}	-6.180^{***}	-6.204^{***}	-1.658^{***}
	(0.325)	(0.291)	(0.317)	(0.075)
Population (000s)	-0.086^{***}	-0.022	0.019^{**}	0.068^{***}
	(0.015)	(0.013)	(0.006)	(0.002)
Population 1 mile (000s)	0.002	0.002^{***}	0.005^{***}	0.001^{***}
	(0.001)	(0.001)	(0.001)	(0.000)
HOLC score	0.043	-0.022	0.039	-0.114^{***}
	(0.042)	(0.036)	(0.032)	(0.010)
Ave HOLC score 1 mile	0.104^{**}	0.021	-0.391^{***}	0.112^{***}
	(0.047)	(0.036)	(0.042)	(0.010)
LMI tract	0.338^{***}	0.555^{***}	-0.141^{**}	-0.068^{***}
	(0.077)	(0.048)	(0.061)	(0.011)
Percent household w/ vehicles	-0.019	0.131^{***}	0.127^{***}	0.127^{***}
	(0.033)	(0.030)	(0.032)	(0.007)
Other banks' branches	0.128^{***}	0.100^{***}	0.124^{***}	
	(0.004)	(0.004)	(0.004)	
Percent Black	0.146^{***}			-0.082^{***}
	(0.007)			(0.003)
Percent Black 1 mile	0.015^{***}			
	(0.001)			
Percent Asian		0.151^{***}		0.013^{***}
		(0.017)		(0.003)
Percent Asian 1 mile		0.029^{***}		
		(0.002)		
Percent Hispanic			0.126^{***}	-0.118^{***}
			(0.007)	(0.002)
Percent Hispanics 1 mile			0.007^{***}	
			(0.001)	
Percent White				0.049^{***}
				(0.002)
MDI branches				0.383^{***}
				(0.018)
Scale	0.702	1.143	0.856	3.213
Observations	313151	313151	313151	313151

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A2: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on percent graded D within census tracts				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
(Intercept)	-6.710^{***}	-6.147^{***}	-6.264^{***}	-1.631^{***}
	(0.322)	(0.290)	(0.317)	(0.075)
Population (000s)	-0.071^{***}	-0.025	0.027^{***}	0.068^{***}
	(0.015)	(0.013)	(0.006)	(0.002)
Population (000s)1 mile	0.001	0.003^{***}	0.001	0.000^{**}
	(0.001)	(0.001)	(0.001)	(0.000)
Percent Graded D	-0.010	-0.003	-0.003	-0.072^{***}
	(0.014)	(0.015)	(0.012)	(0.004)
Ave Graded D 1 mile	0.140^{***}	-0.038^{*}	-0.112^{***}	0.079^{***}
	(0.018)	(0.020)	(0.016)	(0.005)
LMI tract	0.301^{***}	0.570^{***}	-0.152^{**}	-0.071^{***}
	(0.079)	(0.047)	(0.065)	(0.011)
Percent households w/vehicles	-0.016	0.130^{***}	0.125^{***}	0.124^{***}
	(0.032)	(0.030)	(0.032)	(0.007)
Other banks' branches	0.125^{***}	0.101^{***}	0.122^{***}	
	(0.004)	(0.003)	(0.004)	
Percent Black	0.141^{***}			-0.083^{***}
	(0.007)			(0.003)
Percent Black 1 mile	0.016^{***}			
	(0.001)			
Percent Asian		0.152^{***}		0.014^{***}
		(0.017)		(0.003)
Percent Asian 1 mile		0.029^{***}		
		(0.002)		
Percent Hispanic			0.121^{***}	-0.117^{***}
			(0.009)	(0.002)
Percent Hispanic 1 mile			0.007^{***}	
			(0.001)	
Percent White				0.048^{***}
				(0.002)
MDI branches				0.384^{***}
				(0.018)
Scale	0.703	1.142	0.891	3.220
Observations	313151	313151	313151	313151

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A3: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on HOLC Score using Meier and Mitchell (2023)				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
(Intercept)	-6.845^{***}	-6.764^{***}	-6.495^{***}	-1.786^{***}
	(0.331)	(0.290)	(0.322)	(0.076)
Population (000s)	-0.180^{***}	-0.010	-0.007	0.070^{***}
	(0.019)	(0.009)	(0.009)	(0.003)
Population (000s) 5 miles	0.000	0.000^{***}	0.001^{***}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
HOLC score	0.061^{*}	-0.032	0.071^{**}	-0.146^{***}
	(0.035)	(0.033)	(0.025)	(0.007)
Ave HOLC score 5 miles	0.193^{**}	-0.009	-0.575^{***}	0.210^{***}
	(0.062)	(0.049)	(0.044)	(0.009)
LMI tract	0.606^{***}	0.652^{***}	-0.165^{***}	-0.070^{***}
	(0.079)	(0.048)	(0.042)	(0.011)
Percent household w/ vehicles	0.025	0.139^{***}	0.135^{***}	0.134^{***}
	(0.033)	(0.029)	(0.032)	(0.007)
Other banks' branches	0.119^{***}	0.109^{***}	0.137^{***}	
	(0.005)	(0.004)	(0.003)	
Percent Black	0.115^{***}			-0.086^{***}
	(0.009)			(0.003)
Percent Blacks 5 miles	0.015^{***}			
	(0.002)			
Percent Asian		0.150^{***}		0.008^{*}
		(0.014)		(0.003)
Percent Asian 5 miles		0.045^{***}		
		(0.002)		
Percent Hispanic			0.063^{***}	-0.115^{***}
			(0.006)	(0.002)
Percent Hispanic 5 miles			0.019^{***}	
			(0.002)	
Percent White				0.048^{***}
				(0.002)
MDI branches				0.382^{***}
				(0.017)
Scale	0.627	1.081	0.811	3.178
Observations	313151	313151	313151	313151

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A4: Poisson GEE Estimates on the count of MDI and non-MDI branches in census tracts with bank branches within all counties with MDIs

Based on percent graded D within census tracts				
	Black MDIs	Asian MDIs	Hispanic MDIs	Other Bank Branches
(Intercept)	-6.791^{***}	-6.720^{***}	-6.612^{***}	-1.684^{***}
	(0.327)	(0.287)	(0.322)	(0.075)
Population (000s)	-0.182^{***}	-0.012	-0.001	0.069^{***}
	(0.019)	(0.009)	(0.009)	(0.003)
Population (000s) 5 miles	0.000	0.001^{***}	0.001^{***}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Percent Graded D	0.047^{***}	-0.026^{**}	0.015	-0.053^{***}
	(0.011)	(0.011)	(0.010)	(0.002)
Ave Graded D 5 miles	0.144^{***}	-0.127^{***}	-0.436^{***}	0.119^{***}
	(0.034)	(0.037)	(0.033)	(0.007)
LMI tract	0.595^{***}	0.677^{***}	-0.186^{***}	-0.086^{***}
	(0.081)	(0.046)	(0.042)	(0.011)
Percent households w/ vehicles	0.030	0.137^{***}	0.135^{***}	0.127^{***}
	(0.032)	(0.029)	(0.032)	(0.007)
Other banks' branches	0.117^{***}	0.115^{***}	0.140^{***}	
	(0.004)	(0.004)	(0.003)	
Percent Black	0.114^{***}			-0.086^{***}
	(0.009)			(0.003)
Percent Black 5 miles	0.016^{***}			
	(0.002)			
Percent Asian		0.153^{***}		0.011^{**}
		(0.013)		(0.003)
Percent Asian 5 miles		0.043^{***}		
		(0.002)		
Percent Hispanic			0.062^{***}	-0.115^{***}
			(0.005)	(0.002)
Percent Hispanic 5 miles			0.019^{***}	
			(0.002)	
Percent White				0.048^{***}
				(0.002)
MDI branches				0.384^{***}
				(0.017)
Scale	0.637	1.083	0.820	3.197
Observations	313151	313151	313151	313151

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$