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The Impact of Labels on Real Asset Valuations*

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Abstract

Expectations and sentiment of economic agents about financial prospects are both the drivers and the leading indicators of economic phenomena. This paper shows that neighborhood labels, frequently used in realtors' property descriptions, have a causal impact on the demand for housing. Results indicate that appraised values, house prices, and rents increased in minority neighborhoods upon removal of neighborhood labels. The underlying mechanism likely works through forming expectations about future growth in housing markets, as documented by the decrease in the rent-to-price ratio and lack of change in the creditworthiness of the neighborhood residents.

JEL Classification: G50, G41, G12, R31, O18

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I. Introduction

The impact of labels and perception on asset valuation has recently been introduced in the finance literature and practices. Examples include environmental, social, governance, and sustainability labels impacting valuation of assets and firms (Nagaraj and Stern, 2020; Boyer, 2011; Goldsmith-Pinkham et al., 2023). Building on a growing body of literature showing that risk perception can be driven by factors other than volatility, we explore whether and how labels affect the valuation and rate of return on housing, the largest single component of most household's wealth.

In this paper, we examine how labels and perception are priced into the housing market and quantify the real economic impact implied through forming expectations about future growth in housing market. We focus on housing valuation in minority neighborhoods, due to the recent evidence of racial disparities in the mortgage collateral valuation process (Ambrose et al., 2021) and returns to homeownership (Diamond, Stanford and Diamond, 2024). Although federal law prohibits various forms of discrimination when valuing real assets, social stigma and expectations during the housing selection process may nevertheless carry racial undertones and have a real impact on valuation for particular housing locations and property financing options—as evidenced by the long-standing racial and ethnic differences in access to home ownership and mortgage markets (Goetzmann, Spaenjers and Van Nieuwerburgh, 2021).

Following the Black Lives Matter movement, in 2020, the National Association of Realtors reaffirmed its commitment to fair and equitable housing (NAR 2020). In response, several local realtor associations chose to remove neighborhood classifications from their Multiple Listing Services (MLS) platforms, following concerns that the neighborhood labels in the MLS are outdated and reflect historical government maps that were used to define redlined areas. We show that the removal of neighborhood labels led to increased demand for housing and to a lower rate of return in affected minority neighborhoods.

Using granular data and two empirical approaches—a triple-difference model and an event study model—we demonstrate that minority neighborhoods experienced greater demand for housing, consistent with higher house prices and lower capitalization (cap) rates, after the removal of the neighborhood labels. We also provide evidence that the default risk—as measured by the Equifax Risk Score of residents in the affected areas—did not change. Combined, the lower cap rates and the lack of change in the underlying creditworthiness of neighborhood residents indicate that the mechanism of increased demand due to the censorship of MLS labels likely works through expectations of higher future growth in housing markets.

MLS platforms are used in real estate transactions to reduce the information frictions in housing markets. Importantly, the platforms provide numerical codes denoting MLS neighborhood boundaries ("MLS Labels").[1] Some MLS labels used today allegedly reflect maps used in the past for rank-ordering neighborhoods in terms of mortgage lending risk (formerly known as "security maps").[2] Although MLS labels today do not rank neighborhoods the same way the security maps did in the past, the motivation to remove them suggests that MLS labels are being misused to rank neighborhoods and potentially affect real outcomes.

We conjecture that the MLS labels impact housing markets by contributing to expectations about future housing outcomes. We hypothesize that removal of MLS labels weakens the reputation effects of labels on house prices and rents, i.e., on demand for housing. In

[1] There are about 500 MLS platforms used in real estate transactions across the United States. Most of the platforms use "Area" fields to label neighborhoods, allowing MLS users to filter property searches. See `https://ddwiki.reso.org/display/DDW17/MLSAreaMajor+Field`, and `https://ddwiki.reso.org/display/DDW17/MLSAreaMinor+Field`.

[2] See https://mobilerealtors.com/.

particular, once MLS labels are removed and appraisers and real estate agents cannot use the labels to locate properties for comparable valuations or property searches, properties that were previously devalued due to their location in specific MLS areas may no longer face such disadvantages. On the other hand, if market participants gather the same information about neighborhoods from other sources, then the availability of MLS labels should have no impact on real outcomes.

To investigate this hypothesis, we exploit the MLS label censorship that occurred during 2021Q3 in Las Vegas, Nevada—the only metropolitan area in the United States where the change was not anticipated and announced.[3] The extent of MLS usage before the change and the unanticipated nature of this change created a natural laboratory for testing the impact of MLS label removal on housing and neighborhoods. The MLS in Las Vegas has three attributes that make it an especially suitable laboratory for the empirical analysis: (i) it is the dominant platform for the entire Southern Nevada region, (ii) its labels were widely used and repeatedly shared by local realtors, and (iii) to the best of our knowledge, it is the only locally dominant exchange that *discreetly* removed the MLS labels.

Since appraisers rely on MLS platforms to find comparable sales for lending valuations, we first examine the influence of MLS labels on appraisal practices. We use nationwide census tract-level data on single-family residences from the Federal Housing Finance Agency (FHFA) Uniform Appraisal Dataset (UAD) Aggregate Statistics, the most comprehensive, publicly available dataset on appraisals. To account for possible confounding events, we use the K-nearest neighbor technique to match each property's location census tract in Las Vegas (i.e., Clark County, Nevada) to comparable census tracts in other parts of the nation in a

[3] At least two other realtors' associations in the United States removed the MLS neighborhood labels from usage. Realtors in Atlanta, Georgia, and Mobile, Alabama, *voted* to remove the Area field in 2021 with an effective date as late as 2023; this change was announced and anticipated. See https://www.gamls.com/blog and https://mobilerealtors.com/.

triple-difference model. The three differences are (i) Las Vegas census tracts vs. matched control tracts, (ii) observations before and after the censorship of MLS labels, and (iii) the cross-sectional intensity of minority households in census tracts. We match on various pre-treatment demographic characteristics, mortgage trends, and house price growth patterns. The results indicate that the average appraised value increased by about 7.2% (or $26,400) in treated high-minority tracts compared to counterfactual (control) tracts from 2020 to 2022, following the censorship of the MLS labels.[4]

We further analyze the average *distance* between the subject property and comparable sales in appraisals. The results indicate that after the censorship of the MLS neighborhood labels, the distance between appraised properties and their respective comparables increased in treated minority tracts relative to counterfactual tracts by about 2.4%. Moreover, we observe that post-censorship, properties selected as comparables are more likely to be in a different census tract than their subject property in affected minority neighborhoods. These findings suggest that the choice of comparable property sales by appraisers was previously limited by the availability of the MLS labels and this limit has become less binding.

There may be a concern that the increased distance between subject and comparable properties is a mechanical result in the sense that there may simply not have been enough comparables in the minority tracts. We alleviate this concern by analyzing the *number* of completed purchase appraisals. The results indicate that the number of appraisals supporting property acquisitions increased after the censorship of the MLS labels in treated minority tracts relative to counterfactual tracts. Hence, a lack of liquidity in minority tracts does not explain our findings on distance.

The result of increased appraisal values is indicative of increased demand, yet it may

[4] Our specification accounts for changes in the home price and rent gradients due to the Covid-19 pandemic, as documented by Gupta et al. (2022).

coincide with other neighborhood changes. To this end, we estimate the direct effect of censoring the MLS labels on individual-property prices utilizing (i) the variation in timing of MLS label censorship across properties and (ii) repeat sales and repeat lease transactions within Clark County, Nevada, from 2013 to 2022.

Specifically, in an event study setting, we compare the average response of neighborhoods with a high share of minority residents to that of mostly White areas over time from the MLS label censorship date (2021Q3) using *repeat transactions* and controlling for lagged, time-varying neighborhood characteristics.[5] The results indicate (i) the absence of a price differential between the minority and non-minority census tracts before the censorship date—consistent with the parallel pre-treatment trend assumption—and (ii) an increase in closing prices of up to 22% ($61,914) in sales contracts and 10% ($146.40 per month) in lease contracts in minority neighborhoods relative to non-minority neighborhoods during the post-period.

The event study method allows us to analyze sales and rents in minority neighborhoods before and after the censorship date, but it is not flexible enough to test for the heterogeneity of this effect or to account for neighborhood-specific trends. Therefore, in the next step, we use a difference-in-difference analysis, where the first difference comes from the timing of the property-level censorship and the second difference is taken from the variation between minority and non-minority neighborhoods. In this setting, we are able to strengthen the event study results by controlling for location-time fixed effects and/or time-varying census tract-level attributes in addition to property-level effects.

With this setup, we confirm the direct and causal impact of MLS label removal on increased home sale prices and rents. Prices net of neighborhood-specific trends in high-

[5] The *MinorityShare* is set as the share of residents who are not non-Hispanic White in an MLS neighborhood area, according to the 2014-2018 American Community Survey's five-year estimates.

minority-share areas increased by 10% ($30,952) in sales contracts and 12% ($175.68 per month) in lease contracts for properties no longer bearing MLS labels. The effect is linearly increasing with the share of the minority population in census tracts. When segmenting areas by race, we observe that the sales price increased by 23% in Black tracts and by 17.3% in Hispanic tracts but decreased by 15.8% in Asian and Pacific Islander tracts, all relative to White tracts, after censorship of the MLS labels. We observe similar dynamics in lease contracts. We also find that the impact of labels on neighborhoods occurs mostly at the peripheries of the neighborhoods, where the label boundaries begin to blur.

To better understand the underlying causal mechanisms of the MLS labeling effects on housing demand in minority neighborhoods, we examine the behavior of *individual* economic agents (buyers and renters) in housing markets. To do so, we estimate rent-to-price ratios (i.e., cap rates) using a two-stage approach in which we impute the rental price for each sales transaction using rental data. We observe that cap rates decreased in minority areas after censorship, suggesting a change in the expectation of price growth by market participants or a change in the perception of risk incurred from fluctuations in cash flows.

We conjecture that the impact of labeling on housing demand works through expectations of future growth of minority neighborhoods. To this end, we investigate several potential mechanisms related to this effect. One potential mechanism underpinning the impact of MLS label removal on housing valuations and outcomes is change in neighborhood composition. To examine this hypothesis, we explore the changes in the racial composition of minority tracts in Las Vegas compared to control tracts post-censorship. We show that the share of non-Hispanic White home purchase mortgage applicants increased post-censorship in high-minority tracts using a triple-difference approach. Those applicants also have higher incomes and are older, which suggests that removing neighborhood labels attracted more affluent individuals to purchase homes in minority neighborhoods that they otherwise may not have considered.

To further investigate the changes in neighborhood characteristics, we explore mobility into and out of the treated areas as well as individual characteristics of creditworthiness (summarized as the Equifax Risk Score) of individual movers and non-movers using dynamic individual-level data from a major credit bureau. We first show that in-migration increased and out-migration decreased. Specifically, the results indicate that treated high-minority tracts attracted a 2.8 percentage-point increase in the number of consumers that moved into treated high-minority tracts in 2022 compared to control tracts, representing a 16.4% increase in the base rate of in-migration (approximately 17%). We also show a significant decline of one percentage-point in out-migration from treated high-minority tracts in 2022 compared to counterfactual tracts, representing a 9% decline in the base rate of out-migration (approximately 11%). Lastly, we show a modest but significant decline of 1.7 in the average Equifax Risk Score for affected minority tracts when compared to unaffected tracts elsewhere in the country, representing a 0.3% decline in the base Equifax Risk Score. This implies that the house price increases from the censorship of MLS labels can be attributed to a change in market participants' perception of the growth in and demand for minority neighborhoods, not the risk profile of residents in the neighborhoods.

Overall, the combination of the results showing (i) a decline in residential cap rates, (ii) an increase in housing demand, and (iii) no significant change in the overall riskiness of the individuals living in or moving into the treated areas suggest that the impact of labels on neighborhoods is likely working through market participants' formation of expectations about future house price growth and overall improvement in the housing markets of the treated areas.

Our study contributes to several major strands of literature. First, we build on studies about real and private asset valuation. We show that households' investment choices in the housing market may be driven by subjective classifications of neighborhoods in a way that influences expectations about price appreciation. Related work on house price expectations includes Piazzesi and Schneider (2009), Burnside, Eichenbaum and Rebelo (2016), Glaeser and Nathanson (2017), Bailey et al. (2018), Armona, Fuster and Zafar (2019), Kuchler and Zafar (2019), Bottan and Perez-Truglia (2020), and Liu and Palmer (2021). Second, our paper presents a mechanism that may be a contributing factor to the financial wealth inequalities emphasized by Bach, Calvet and Sodini (2020), Kuhn, Schularick and Steins (2020), and Fagereng et al. (2020), as expectations about house prices are critical in household finance decisions. The premise behind such a mechanism is that neighborhood choices have a substantial impact on residents' overall life experiences. For example, Chetty, Hendren and Katz (2016) show that growth patterns in an area affect the educational outcomes of children, and Lovenheim and Mumford (2013) demonstrate that those same price growth patterns influence family planning and fertility choices. Yet factors that influence beliefs about price expectations are understudied.

Additionally, we contribute to recent studies in the finance literature on racial and ethnic differences in various stages of the home-buying process including interactions with real estate agents (Ondrich, Ross and Yinger, 2003; Agarwal et al., 2019; Hanson and Hawley, 2023), lenders (Ambrose, Conklin and Lopez, 2021; Bartlett et al., 2022; Frame et al., 2021; Giacoletti, Heimer and Yu, 2021; Bayer, Ferreira and Ross, 2018), and appraisers (Howell and Korver-Glenn, 2018; Ambrose et al., 2021; Avenancio-León and Howard, 2022). Tangential work includes studies on the influence of neighborhood grading in security maps by the now-defunct Home Owners' Loan Corporation and the Federal Housing Administration in the

1930s (e.g., Jackson, 1980; Holmes and Horvitz, 1994; Tootell, 1996; Hillier, 2003; Fishback, 2014; Aaronson, Hartley and Mazumder, 2021; Aaronson et al., 2021; Fishback et al., 2023) Our paper demonstrates that in high-minority neighborhoods, MLS labels suppress demand for housing, limit the set of properties from which buyers and renters may choose and limit which properties appraisers choose as comparisons.

From a policy perspective, our paper speaks to the active debate on the role of race in the mortgage appraisals. Following anecdotes of racial discrimination in appraisal in the mortgage market during the Covid-19 pandemic, the Biden Administration put together the Property Appraisal and Valuation Equity task force (`https://pave.hud.gov/`), which aims to "root out" racial appraisal bias. State governments including the Illinois legislators established their own task forces, too.[6] However, there are only a few studies in this area and a consensus has not yet been establish. Ambrose et al. (2021) show that collateral for refinance mortgages issued during the subprime era were systematically undervalued for Blacks and Hispanics by 0.6% to 4%, regardless of the appraiser's race. Williamson and Palim (2022) demonstrate a continued undervaluation for minority-owned homes of a similar magnitude in conventional refinance mortgages issued from 2019 to 2020. Perry, Rothwell and Harshbarger (2018) and Freddie Mac (2022) also provide evidence that homes in minority neighborhoods are undervalued compared to white owned homes. By contrast, researchers at the American Enterprise Institute (Pinto and Peter, 2021, 2022, 2023) argue that incidents of racial discrimination in appraisals may exist but are minor. We demonstrate that an institutional feature in the appraisal and real estate brokerage industries opposed to individual actions of racial animus oppressed property values in minority neighborhoods.

Lastly, our work contributes to a growing body of literature in finance showing that the

[6] See `https://govappointments.illinois.gov/boardsandcommissions/details/?id=b316cb5e-2007-ee11-8f6d-001dd8068008`.

returns on assets can be driven by factors other than volatility and risk perception. The impact of labels and beliefs on valuation of assets has recently been introduced in the finance literature and practices (e.g., Boyer, 2011; Baldauf, Garlappi and Yannelis, 2020; Bakkensen and Barrage, 2022). We build on this literature by exploring how labeling affects real estate values, the largest single component of household's wealth.

II. Background on Realtors and Neighborhood Labels

During the Great Depression, realtors filled out surveys about neighborhood desirability that were used by government agencies to create color-coded security maps with which to determine lending risk assessment (Aaronson, Hartley and Mazumder, 2021; Fishback et al., 2023). One notorious feature of the security maps is that predominately Black neighborhoods were shaded in red and given a "D" grade label. This practice became known as redlining. Additionally, realtors steered buyers and tenants away from lowest graded areas, underselling Black and Hispanic neighborhoods (Hartley and Rose, 2023; Aaronson et al., 2023).[7] Today, real estate agents affiliated with the National Association of Realtors prominently display literature on the U.S. fair housing laws in their brokerage offices; undergo comprehensive training on local, state, and federal fair housing laws; and face strict penalties if they fail to adhere to those regulations.[8]

Despite these advances in fair housing, studies continue to find evidence of racial disparities in house prices (Perry, Rothwell and Harshbarger, 2018; Howell and Korver-Glenn, 2018, 2020; Williamson and Palim, 2022; Avenancio-León and Howard, 2022) and access to credit (e.g., Crosignani and Le, 2023). Furthermore, an extensive body of academic litera-

[7]Additionally, private lenders were overly cautious about extending credit to buyers who wished to purchase homes in the neighborhoods that were color-coded red (Hillier, 2003).
[8]See https://cdn.nar.realtor/.

ture has linked the security map boundaries to differences in pollution, police violence, food deserts, and broadband access, as well as the allocation of apartments, tobacco retailers, and oil and gas wells (see Markley, 2023). These studies call into question the persistence of discriminatory practices like redlining.

In summer 2020, following the death of George Floyd and a nationwide movement spotlighting racial oppression and police violence, the president of the National Association of Realtors spoke on behalf of the industry, declaring that realtors' past actions were "shameful" and "we are sorry" (NAR 2020). Subsequently, realtor associations in California, Georgia, Illinois, Minnesota, and Missouri issued their own formal apologies, calling for change.[9] To take action, realtors in Atlanta, Georgia, and Mobile, Alabama, voted to remove the Area field—which codes neighborhoods into geographic boundaries—of their local MLS platforms, responding to concerns that the MLS labels are relics of search practices that predate the digitization of MLS catalogs and perhaps overlap with outdated boundaries such as those from the redlining security maps.[10] The Las Vegas Realtors (LVR) organization similarly removed MLS labels in the third quarter of 2021, but it did so without making an announcement.

We find evidence supporting the concerns that MLS labels may have perpetuated the historical perceptions of certain areas. For example, Area 101 in the LVR-MLS area map shown in Figure 1 falls within the boundaries identified by local politicians and civil rights advocates as a zone allegedly subjected to illegal redlining in the 1970s (see Figure A.1 and the Robert "Bob" Price Political Papers, 1959-1988). This area includes the historical Westside neighborhood, the only neighborhood in Las Vegas in which Blacks were allowed to live during the 1940s and 1950s. Conversations we had with local real estate agents hinted that Area 101 is today considered one of the least desirable neighborhoods in Las Vegas.

[9] See https://www.nareb.com/press and https://www.chicagotribune.com.
[10] See https://www.gamls.com/blog and https://mobilerealtors.com/.

III. Data

A. FHFA Appraisals, HMDA Statistics, and ACS Demographics

We obtain annual census tract data on appraisals from the FHFA UAD Aggregate Statistics files. These data provide a comprehensive overview of nationwide appraisals of single-family residences for purchase and refinance mortgage transactions received by Fannie Mae and Freddie Mac from 2013 to 2022 (independent of whether the mortgages were conforming loans). We focus on the mean appraised value in log form, the average distance between the subject property and comparable sales in log form, the proportion of comparable sales in the same census tract as the subject property in decimal form, and the count of appraisals for purchase transactions. Moreover, we calculate the pre-trend growth as the five-year average change in the mean appraised value for each tract, covering 2015 to 2019. We complement these data with data on rejection rates for conventional and FHA mortgages from the 2018 Home Mortgage Disclosure Act (HMDA) files.

Additionally, we merge the appraisal data with census tract data from the Census Bureau's American Community Survey (ACS) 2014–2018 five-year estimates.[11] We retain the tracts that persist from the 2010–2020 decennial tract configurations to mitigate concerns that a change in neighborhood quality rather than a change in neighborhood classification influences our analysis.[12] As the treatment group is defined by the LVR-MLS coverage area,

[11] The ACS variables that we collect data on are Median Home Value (B25077_001E), Median Gross Rent (B25064_001E), Median Family Income in the Past 12 Months (B19113_001E), Total Population (B01003_001E), Hispanic or Latino (B03002_012E), White Alone (B03002_003E), Black or African American (B03002_004E), American Indian and Alaska Native Alone (B03002_005E), Asian Alone (B03002_006E), Native Hawaiian and Other Pacific Islander Alone (B03002_007E), Some Other Race Alone (B03002_008E), and Two or More Races (B03002_009E). We also collect data on Owner Occupied Households (B25003_002e), Renter Occupied Households (B25003_003E), Housing Units (B25002_001E), Occupied Units (B25002_002E), and Vacant Units (B25002_003E).

[12] Typically, census tracts that have high population growth are split into new tracts, and those that experience the opposite are likewise grouped.

we focus on tracts in Clark County, Nevada. The control tracts are those elsewhere in the nation.[13] We remove census tracts that have missing values for the selected characteristics, leaving 410 treated tracts and 48,407 control tracts in the final tract-level sample.

Panel A of Table I reports the summary statistics, t-test results, and Cohen's d-statistics for the treated and control tracts.[14] The reported appraisal statistics are current as of 2020. We observe stark differences between the treated and control groups. For this reason, we perform propensity score matching in Section IV.A to identify an adequate comparison group.

A.1. HMDA Data and FRBNY Consumer Credit Panel (CCP) /Equifax Data

HMDA data capture the vast majority of home mortgage applications and approved loans in the United States, including loans to individuals and business entities. The data provide numerous characteristics of each loan and its borrower. We use the data to explore changes in the neighborhood composition of the treated MLS and to test for differences in migration patterns, as we discuss in Section V.B.

We obtain an additional dataset for use in the analysis called the "NY Fed Equifax Consumer Credit Panel" (CCP) dataset. The CCP dataset is a nationally representative sample of Equifax credit report data. This dataset tracks all consumers with a US credit file residing in the same household from a random, anonymous sample of 5% of US consumers with a credit file.[15] The panel nature of the data allows us to observe when someone has

[13] We remove from the control sample states that may have been affected by the removal of their own MLS Area field, including Alabama, Arizona, Georgia, and Louisiana.

[14] Cohen's d-statistic is a measure of economic significance calculated as the mean difference divided by the pooled standard deviation. By convention, a d-statistic that in absolute terms is 0.2 or less is considered to have a small effect size.

[15] Although this paper categorizes census tracts based on racial composition, it does not use any individual-level racial information from the CCP data, as it does not contain information about consumers' race or gender. For more information about the FRBNY CCP, see https://newyorkfed.org.

migrated and is living in a census tract different from the one they were living in at the end of the preceding quarter.

B. MLS Data Sample Selection

We collect data on transactions from the LVR-MLS. The data contain detailed information about contract terms, property characteristics, and neighborhood amenities. We also, and more importantly, observe the reported MLS Area for each property before the censorship date. MLS rental data are collected by listing date from August 2008 to December 2022, amounting to more than 456,000 observations. Similarly, MLS sales data are collected by sales date from January 2006 to December 2022, resulting in more than 679,000 observations.[16] We remove approximately 3,214 (0.7%) rental observations and 18,289 (2.7%) sales observations that are missing an 11-digit parcel number that uniquely identifies the property. We use the parcel numbers to merge the MLS data with various files from the Clark County Assessor's Office to collect additional information on properties' structural characteristics and location such as geo-coordinates and census tracts. Furthermore, we focus on transactions for single-family, condominium, and two- or more-unit (e.g., duplex, triplex, and quadruplex) residences, excluding manufactured housing and properties classified as "Other."[17]

We remove records of properties with a sales contract price that is above $1,100,000 or below $30,000, properties with a monthly rental contract rate that is above $10,000 or below $300, properties with a living area larger than 6,000 square feet or smaller than 400 square

[16] Lopez and Yoshida (2022), Lopez, McCoy and Sah (2022), and Lopez (2021, 2022) examine subsets of these sales and rental data.

[17] Note that we also merge the MLS data with census tract data from the U.S. Census Bureau's American Community Survey (ACS) five-year estimates that have an ending year from 2010 to 2019 with a lag of three years behind the lease or sale closing date as the MLS data are coded (by the data provider) to the 2010 census tract definitions.

feet, properties with a lot size greater than 50,000 square feet, properties with more than six bedrooms or bathrooms, properties with more than four car spaces in a garage, properties with more than four fireplaces, and properties with a building age of more than 60 years. Additionally, for the MLS rental data, we exclude withdrawn listings (those that did not result in a fully executed contract) and outlier rental listings (those that offered a referral commission of more than $7,000). Lastly, we drop observations with an imputed MLS Area classification of 800 or higher.

The final sample consists of 357,980 sales contracts and 258,341 rental contracts, which account for more than 93% of the fully executed sales and lease contracts for single-family, condominium, and 2+ unit properties from January 2013 to December 2022.

C. MLS Summary Statistics

Table II reports summary statistics of properties' close prices, structural characteristics, and the proportion of these contracts that were for listings that did not report their MLS Area labels. The average closing price is $281,428 in sales contracts and $1,464 per month in rental contracts, implying an average cap rate of approximately 6.24%.

Figure 4 displays the market trends among sales and leases from 2013 to 2022, including the number of transactions and average closing prices. As Figure 4 shows, the number of sales peaked at more than 40,000 in 2021 but fell to fewer than 30,000 in 2022. By contrast, the annual number of leases fell to a trough in 2021 but increased slightly in 2022. LVR discontinued the use of the MLS Area label in August 2021, leading to an increasing share of transactions closing without ever having reported it. By the end of 2022, virtually all sales and lease transactions closing did not report the MLS Area in their listing sheets. These transactions jointly account for 10% of the sales and 9% of the leases in the final sample.

Meanwhile, from 2020 to 2022, the average sale price per square foot increased by 41%, and the average rent per square foot increased by 24.8%. As the Covid-19 pandemic-related shutdowns began in March 2020, sparking increased demand for space in low-density neighborhoods away from downtown locations (D'Lima, Lopez and Pradhan, 2022; Van Nieuwerburgh, 2023), we account for these market dynamics in our analysis.

D. MLS Areas

To the best of our knowledge, no publicly available shapefile outlines MLS Area boundaries. However, as each observation in the sales and rental data reveals the geographic opinion of real estate agents, we impute the MLS Area by census tract and plot the results in Figure 2(a).[18] To better understand the demographic distribution across MLS Areas, we link to area information about each census tract from the U.S. Census Bureau's ACS five-year estimates, 2014– 2018. As such, we color-code the treated census tracts by minority population share in Figure 2(b). The share of minorities is calculated as

$$MinorityShare = 1 - \text{White Alone}/\text{Total Population}$$

where White Alone is the population that identifies as not Hispanic when asked about ethnicity and as White when asked about race in government-prompted questions. Figure 2(b) shows that census tract populations in the northeast areas have a minority share that

[18]To impute the MLS Area by census tract, we use every single record in the rental and sales MLS data regardless of whether it is used in the final sample, provided that the MLS Area label is not missing. The combined data amounts to more than one million MLS records. Figure A.3 in the appendix plots the LVR-MLS data and color-codes observations by reported MLS Area class. We then spatially join the mode-reported MLS Area for each tract to the 2010 TIGER/Line shapefile for Clark County, Nevada, from the U.S. Census Bureau. Lastly, we manually adjust the MLS Area class for selected census tracts to match the official MLS Area map in Figure 1. The final MLS Area classifications are shown in Figure 2(a).

falls between 60% and 98%. Figures 2(c) and 2(d) illustrate the geographic distribution of the residential median home value and median gross rent, respectively. In both figures, lower values frequently occur in census tracts with high minority shares. Property values and rents are greater along the western and southern peripheries than in the central and northeastern areas.

For each revealed MLS Area depicted in Figure 2(a), we compute the population-weighted-average median property value and median gross rent by year, using census tract population statistics. Likewise, we find the population-weighted-average minority share of the MLS Area, which defines the treatment intensity in our analysis. We examine the relationship between price, rent, and minority share at the MLS Area level in Figures 3(a) and 3(b). There is a negative correlation between the median price and minority share ($\rho = -0.71$). The rent also correlates negatively with the minority share ($\rho = -0.55$). The figures indicate that MLS Areas with primarily non-White residents have lower property values and are more affordable than MLS Areas where the residents are primarily non-Hispanic White.

In Table A.1 in the appendix, we report additional population-weighted-average MLS Area demographics. The renter-to-owner occupancy ratio correlates positively with the minority share ($\rho = 0.39$), while MLS Areas with high minority shares tend to have a low median family income ($\rho = -0.73$). However, the vacancy rate does not move in an obvious direction with the area minority share, as the correlation is weakly positive ($\rho = 0.13$).

IV. Analysis

A. Appraisal Patterns

If appraisers use MLS neighborhood labels as a determining factor when selecting properties for comparison, the availability of an MLS label search filter may influence their selection criteria. To test this hypothesis, we compare the appraisal statistics for each census tract in Clark County to a similar census tract elsewhere in the country along two dimensions: (1) the minority share of the population, and (2) the year before and after the MLS Area label was censored on the LVR-MLS platform. The model is

$$\begin{aligned} A_{k,t} = &\gamma_0 Post \times MinorityShare_k + \gamma_2 Post_t \times Treatment_k \\ &+ \gamma_3 Post_t \times Treatment_k \times MinorityShare_k + \tau_t + \zeta_k + \varepsilon_{k,t} \end{aligned} \tag{1}$$

where $A_{k,t}$ is an appraisal statistic (i.e., log mean appraised value, log mean distance between subject property and comparable properties, share of comparable properties in the same tract as the subject property, and count of appraisals for purchase mortgages) for census tract k during year t; $MinorityShare_k$ is the share of minorities in the census tract; and $Treatment_k$ is an indicator variable for whether the tract is in Clark County. $Post_t$ takes the value of one if the observed year is 2022 and zero if the observed year is 2020. We also include year fixed effects (τ_t) and census tract (ζ_k) fixed effects.

We select comparable census tracts as controls using propensity score matching on the nearest neighbor, where scores are predicted using a probit regression model of $Treatment$

on census tract characteristics. The model is

$$Probit(Treatment_k|Z_k) = \Phi(Z_k\Gamma) \tag{2}$$

where Z_k includes the natural log of median family income, the natural log of median gross rent, Hispanic share, Black share, Asian and Pacific Islander share, vacancy rate, renter-to-owner occupancy ratio, conventional mortgage application rejection rate, FHA mortgage application rejection rate, and five-year average growth rate (2015-2019) in appraisal valuations for census tract k. Γ is a vector of coefficients to be estimated. We retain the same control census tracts for the pre- and post-periods.[19]

Table A.4 in the appendix reports the coefficient estimates of equation (2). Figure A.4 shows the distribution of matched tracts by state, indicating that approximately 35% are in California, 12% are in Florida, and 9% are in Texas. Panel B of Table I reports the post-matching summary statistics, t-test results, and Cohen's d-statistics between the treated and control tracts. We observe that differences in demographic characteristics and the mortgage rejection rate are statistically insignificant or have a small effect size. Furthermore, we observe that the average growth rate in appraisal valuations of the treatment tracts is economically similar to that of the control tracts as the effect size difference is small, which is a condition consistent with the implicit parallel trends assumption.

Table III presents the effects of MLS labeling on appraisals in minority tracts in Clark County relative to similar minority tracts elsewhere in the nation. We report robust standard errors that are clustered by county. Column (1) shows that appraisal valuations increased by

[19]We allow up to 10 matches per treatment tract, apply a caliper of 0.01 on propensity score matches, allow for sampling with replacement, and require common support. We observe that 1 treatment tract and 90 control tracts do not have appraisal records in the post-period, and thus, examine alternative matching parameters in Figure A.5.

about 7.2% (approximately $26,400) in the treated minority tracts compared to the control minority tracts. This effect is statistically significant at the 1% level and lends external validity to the previous findings. Meanwhile, columns (2) and (3) suggest that appraisers began to use different selection criteria for properties in minority neighborhoods. The mean distance between the subject property and comparable sales increased by 2.4% more in the treated minority tracts than in the control minority tracts with statistical significance at the 1% level. Similarly, we observe a relative decrease in the share of comparable sales that are in the same census tract as the subject property in the treated minority tracts. Lastly, column (4) reveals that the number of appraisals for purchase transactions increased during the post-period in treated minority tracts compared to control minority tracts, suggesting that a decrease in the liquidity of property transactions cannot explain the observed outcomes.

Figure A.5 shows estimates of the average response to censorship as the k number of nearest matches selected in building the control sample is increased from 1 to 50 per treated tract for each appraisal outcome. We observe a trade-off between a potential bias toward zero and the variance with an increasing selection of k-neighbors, suggesting that the results in Table III are lower-bound estimates.

B. *Temporal Patterns*

To understand the evolution of market trends across minority neighborhoods around the Area label censorship date, we examine time-varying cross-sectional differences in price with respect to the share of minorities in an MLS Area, as measured using the LVR-MLS data.[20]

[20] We report the *MinorityShare* for each MLS Area in Table A.1 in the appendix.

Specifically, we estimate the following event study model:

$$Y_{i,t} = \sum_l \theta^l (MinorityShare_a \times TimeSinceCensorship^l_{i,t}) + X_{i,t}\beta + \tau_t + \alpha_i + \varepsilon_{i,t} \qquad (3)$$

where $Y_{i,t}$ is the log close price of property i put on the market at time t and $MinorityShare_a$ is the minority share of MLS Area a where property i is located (see Table A.1).

$TimeSinceCensorship^l_{i,t}$ is an indicator of whether property i at time t was put on the market in the l^{th} quarter after the MLS labels were censored, which is 2021Q3.[21] $X_{i,t}$ stands for time-varying census tract characteristics such as the natural log of the median gross rent, cap rate, Hispanic share, and Black share.[22] We account for common changes in the economic environment with year-quarter fixed effects (τ_t) based on the listing date and static idiosyncratic factors with property fixed effects (α_i). Lastly, $\varepsilon_{i,t}$ stands for the error term.

Table A.2 reports the results, and Figure 5 illustrates the average treatment response of minority neighborhoods to the censorship of MLS labels for sales in Panel A and leases in Panel B. While we use the full sales sample in column (1), we set the sample of leases to 2020Q1–2022Q4 in column (2). Property leases occur more frequently than property sales, which allows us to confine the sample period to the years of the pandemic. The results indicate that prices for sales and leases in minority neighborhoods increased starting in 2021Q3 relative to prices in 2021Q2. The average response in sales grew from 4% in 2021Q4 ($l = 0$) to 22% in 2022Q4 ($l = 5$) in minority neighborhoods compared to White neighborhoods. The average response in leases ranged from 9% to 10% during the ex-post years following 2021Q3 ($l \in [1, 5]$). Prices in minority neighborhoods did not change relative

[21] $l \in \{-6+, -5, -4, -3, -2, 0, 1, 2, 3, 4, 5\}$ The base period where $l = -1$ is 2021Q2 such that the event time $l = -2$ is 2021Q1, $l = 0$ is 2021Q3, $l = 1$ is 2021Q4, and so on. The event time $l = -6+$ indicates the property was put on the market six or more quarters before 2021Q3.

[22] The cap rate is measured as the annualized median gross rent divided by the median home value. The census tract characteristics are the ACS 5-year estimates lagged by three years from the closing year.

to prices in White neighborhoods during the few quarters preceding 2021Q2, supporting the implicit parallel trends assumption of the event study framework. Two F-tests of joint significance indicate that the pre-trend effects are statistically insignificant from event time $l = -5$ to $l = -2$ for sales and from $l = -6$ to $l = -2$ for leases.

However, one concern is that if the counterfactual price evolution response varies based on the demographic composition of neighborhoods, the parallel trends assumption may not hold. Put differently, Black and Hispanic neighborhoods might have grown at different rates than White neighborhoods in the absence of MLS label censorship. Hence, to qualify the causal interpretation made based on the event study framework, we examine sensitivity to possible violations of the parallel trends assumption.

Figures 5(c) and 5(d) show various confidence bounds for event time $l = 5$ following the "conditional-least favorable (C-LF)" confidence bounds method developed by Rambachan and Roth (2023). For the confidence interval set to include zero, $\overline{M}$ must exceed 10% of the observed linear trends in the pre-treatment period for sales and 20% for leases, where $\overline{M}$ is the pre-treatment trend multiplier. This is consistent with the sharp deviation in the pre-trend coefficient observed at event time $l = -6+$ for sales but not leases. The tests suggest that accounting for neighborhood-specific trends is critical, especially for property sales.

To further qualify the causal interpretation, we note that continuous treatment requires the "strong" form of the parallel trends assumption (see Callaway, Goodman-Bacon and Sant'Anna, 2021). In our context, this assumption is that the average evolution of price growth in repeat transactions across all properties around the censorship date would have been the same as that of properties in a different MLS Area if they had switched locations. We conjecture that the strong parallel trends assumption holds in the short term as the real estate supply is fixed in the short term(DiPasquale and Wheaton, 1992). This assumption is bolstered by the pre-trend stress tests discussed.

C. Spatial Patterns

To analyze the spatial response to the removal of MLS neighborhood labels on real outcomes for minority neighborhoods, we use the following model:

$$Y_{i,t} = \delta_0 Treated_{i,t} + \delta_1 MinorityShare_a \times Treated_{i,t} + X_{i,t}\beta + \tau_{z,t} + \alpha_i + \varepsilon_{i,t} \qquad (4)$$

where $Y_{i,t}$ is the close price, and $MinorityShare_a$ is the minority share of each MLS Area a where property i is located. $Treated_{i,t}$ is an indicator of whether the MLS label is absent for property i at time t. Although censorship of MLS labels began in August 2021, $Treated_{i,t}$ varies by property and time because MLS labels appear to have been phased out over two quarters. Specifically, $Treated_{i,t}$ is zero for all properties advertised for sale on or before 2020, one for those properties listed in 2022, and variable for properties listed in 2021. This allows us to compare the performances of two similar properties marketed for sale or lease during the same quarter but with different levels of information available with regard to MLS labels.[23] Furthermore, we are able to include ZIP-year-quarter fixed effects ($\tau_{z,t}$) to account for market trends that are unique to each ZIP code area z. As before, we also include lagged time-varying census tract characteristics ($X_{i,t}$) and property fixed effects (α_i).

Table IV reports ordinary least squares (OLS) estimates of model (4) using various specifications for the closing price in sales and leases. We first employ a naive model that excludes

[23]The MLS Area label field was phased out equally across all areas simultaneously. Figure A.2 in the appendix shows the proportion of sales and leases listed in 2021 that are missing their MLS labels by month. Table A.3 in the appendix shows that the *MinorityShare* is conditionally unrelated to the likelihood of MLS label censorship, reducing potential concerns about treatment selection.

ZIP code time trends and census tract variables. We then gradually account for these factors. We report standard errors clustered by parcel number for statistical inference in parentheses. Columns (1) to (3) set the dependent variable to the natural log of the sale price and the sample to sales transactions. Columns (4) to (6) use the natural log of the monthly rental rate as the dependent variable and the sample of leases. The coefficient on the interaction term of $MinorityShare_i$ and $Treated_{i,t}$ is positive and statistically significant at the 1% level in each column, implying a sharp increase in the sales prices and rental rates of housing in minority-dominant neighborhoods following the removal of MLS Area labels.

Columns (1) and (4) indicate that the average response of minority neighborhoods to the censorship of MLS labels was a price increase of 32% for sales and 11% for leases, respectively. Columns (2) and (5) each account for neighborhood market trends and show an average treatment response of up to 11% for sales prices and 12% for rental rates, respectively. Columns (3) and (6) incorporate census tract characteristics but indicate that they hardly affect the point estimates.

Next, we examine the censorship response based on proximity to peripheries. We predict that the strongest response for MLS label censorship will occur at the peripheries if the absence of the Area label increases the cost of discerning whether a property belongs to an adjacent Area. To test this hypothesis, we first identify the centroid coordinate for each MLS label by calculating the population-weighted average longitude and latitude coordinates of the census tracts linked to each MLS label. Subsequently, we measure the distance between each property and its corresponding centroid relative to the distance of the property located at the 90th percentile from the center. Lastly, using this relative distance, we estimate the parameters of equation (4) for various subsamples including (1) properties within 25% of the relative distance from the Area centroid; (2) properties between 25% and 75% of the relative distance from the Area centroid; and (3) properties beyond 75% of the relative Area centroid distance. Figures A.6 and A.7 in the appendix illustrate the subsamples for sales and leases, respectively.

The results presented in Table V indicate that the intensity of the censorship response increases as the distance from the centroid grows. In the sales market, the response is insignificant within the central region, but it reaches 12% at the furthest peripheries of minority areas and becomes statistically significant at the 1% level. In the rental market, we observe a similar pattern, but the response at the outermost periphery of minority areas reaches 19%, which is significantly higher than previously estimated. These findings suggest that price responses are influenced by activity near the boundaries of MLS Areas.

D. Robustness

We examine the effect of MLS labels in three different ways to ensure the robustness of our results. First, we split the transactions into three cohorts based on the corresponding properties' locations. Cohort 1 consists of properties located in MLS Areas with a *MinorityShare* between 0% and 49%, Cohort 2 sets the *MinorityShare* between 50% and 74%, and Cohort 3 sets the *MinorityShare* between 75% and 100%. Table VI reports the results featuring the *MinorityShare* as a categorical variable (with below 50% as the base). As Table VI shows, the average response to MLS label censorship grows as the Area Cohort ranking increases. In sales contracts, the censorship response in Area Cohort 3 is 9.9% and statistically significant at the 1% level, whereas for Area Cohort 2, the response estimate is 1.8% and statistically significant at the 1% level. A Wald test indicates that Area Cohort 2's response to censorship is larger than that of Area Cohort 1 at the 1% significance level. Among rental rates, we observe a similar pattern of increasing intensity with the area's minority share.

Second, we identify properties by other economic performance measures including the area's median family income, vacancy rate, and renter-to-owner occupancy ratio. We de-mean and standardize each variable. We then sequentially replace the *MinorityShare* variable in equation (4) with each of these economic performance measures but exclude the ACS tract control variables from the model to avoid over-specification issues including collinearity. We obtained results that are consistent with our prior findings. Properties in areas that had low median income, high vacancy rates, or high renter-to-owner ratios in 2018 experienced increased sales prices after MLS label censorship. We see similar patterns with leases; however, in this model, the vacancy rate is not sensitive to label availability. The results suggest that areas that might have been thought of as distressed or underserved experienced a boom in demand after MLS label censorship, reducing the gap between White and minority neighborhoods.

Third, we use a more granular definition of neighborhoods at allow us to examine variation across the minority racial groups: Hispanic, Black and Asian and Pacific Islander (API). In our baseline model (equation (4)) we set the *MinorityShare* measure to the census tract level by using the 2014–2018 ACS five-year estimates of tract Hispanic share, tract Black share, and tract API share.[24] Table VIII shows that compared to those of White tracts, the prices in both sales and lease contracts increased significantly in Hispanic and Black tracts but not in API tracts when the availability of MLS labels changed. One reason that API tracts have the opposite effects as Black and Hispanic tracts is that they are more wealthy neighborhoods and have a median family income that is above average.[25]

Overall, the results overwhelmingly suggest that the labeling of MLS areas had a real

[24] We exclude the time-varying tract Hispanic and tract Black control variables to mitigate concerns about collinearity.

[25] Tract API Share correlates positively with the Tract Median Family Income, while Tract Black Share and Tract Hispanic Share correlate negatively with Tract Median Family Income.

effect on properties in underserved neighborhoods, especially along the peripheries of MLS Areas.

V. Mechanisms

A. Market Perception

To understand the underlying mechanism, we examine the effect of MLS labels on cap rates, which are also known as rent-to-price ratios. From a theoretical standpoint, cap rates reflect the market's perception of risk due to fluctuations in cash flows and price growth expectations. To obtain cap rates, we use a two-stage approach where in the first stage a hedonic rent model is used to impute the rental rate of each home sold, and the second stage projects the baseline model onto the predicted rent-to-purchase price ratio.

The first-stage model is

$$R_{i,t} = Z_{i,t}\theta + \tau_{z,t} + \epsilon_{i,t} \tag{5}$$

where $R_{i,t}$ is the annual rent per square foot for l property i at time t, $Z_{i,t}$ is an array of property characteristics, θ is a vector of coefficients, $\tau_{z,t}$ stands for ZIP-year-quarter fixed effects, and $\epsilon_{i,t}$ is an error term. We present the first-stage model in Table A.5 in the appendix, which uses MLS rental transactions from 2009 to 2022. We then use parameter estimates to predict the annual rental rate per square foot for properties sold ($\hat{R}_{i,t}$) and calculate the rent-to-purchase price ratio as

$$CapRate_{i,t} = \hat{R}_{i,t}/\text{Sales Price per Square Foot}_{i,t}.$$

In the second stage, we estimate equation (4) but replace the dependent variable with

$CapRate_{i,t}$ on the sample of sales.

Table IX reports the results, which indicate that the cap rate fell by up to 1.6 percentage points in minority areas after censorship, representing an approximately 22% degradation of the median cap rate. This result suggests that investors demand a lower return per dollar invested, perhaps because they have adopted higher price growth expectations or anticipate less risk in rental cash flow fluctuations. In the next section, we investigate the nature of this shift in market participants' perception of minority neighborhoods.

B. Neighborhood Composition

If the absence of MLS labels increases the likelihood that home buyers will purchase a property in an area that they otherwise would not have considered, the neighborhood composition may have changed. To examine this hypothesis, we test for differences in migration patterns using data on first-lien mortgage applications for purchase from the HMDA database. Focusing on the change in the racial composition of mortgage applicants from 2020 to 2022 using the same treated and control tracts from Section IV.A and the triple-difference model described by equation (1), we find evidence that the racial composition of minority tracts changed following the removal of the MLS labels. Panel A of Table XI shows that the share of non-Hispanic White and Black purchase mortgage applicants increased post-censorship in high-minority tracts by up to 6.8% and 0.9%, respectively, while the share of non-Hispanic Asians and Hispanics fell by up to 1.4% and 4.8%, respectively, in the same tracts, compared to counterfactual tracts.[26]

We also examine changes in the average log income and age of purchase mortgage applicants by racial group at the tract-level in Panels B and C of Table XI, respectively.[27] We

[26] Table A.6 presents summary statistics for the treated high-minority tracts in 2020 in the HMDA dataset.

[27] As some racial groups do not purchase in all tracts every year, the number of observations decreases in

find that post-censorship, purchase mortgage applicants have statistically significant higher incomes and are older in high-minority treated tracts than in counterfactual tracts. The results are consistent across race and ethnicity. For instance, White and Black mortgage applicants in minority tracts have an income that is 39% and 32% higher than counterfactual White and Black mortgage applicants in minority tracts, respectively. Moreover, mortgage applicants across all racial categories in minority tracts are 3 to 5 years older than counterfactual mortgage applicants purchasing homes in the same tracts. These findings suggest that removing neighborhood labels led more affluent individuals to purchase homes in minority neighborhoods that they otherwise would not have considered.

C. Migration Patterns and Credit Risk Profiles

Additionally, we explore migration patterns and Equifax Risk Score profiles using the FRBNY CCP/Equifax dataset (CCP). The panel nature of the data allows us to observe when someone has migrated and is living in a census tract different from the one they lived in at the end of the preceding quarter. While HMDA data used in the previous sections include only homeowners with a mortgage, the CCP dataset includes both homeowners and renters, allowing us to better explore migration patterns. We also observe the average credit score (Equifax Risk Score) at the census tract level over time. Hence, we apply the same treated and control tracts from Section IV.A and the triple-difference model described by equation (1) to understand changes in neighborhoods, from 2020 to 2022. The dependent variable is set as either in-migration or out-migration, which is measured using a census tract change analysis. If a customer has a registered change in their census tract code in the last (next) 18, 12, and 6 months, they are marked as an in-migrant (out-migrant) "mover." Likewise,

Panel B and C.

we set the dependent variable as the average Equifax Risk Score in the tract.[28] We limit the age of consumers to be between 18 and 95.

We report the results in Table X. Column (1) shows a 2.8 percentage-point increase in households that moved into treated high-minority tracts in 2022 compared to counterfactual tracts, representing a 16.4% increase in the base rate of in-migration (approximately 17%, see Appendix Table A.7). Column (2) shows a significant decline of one percentage-point in out-migration from treated high-minority tracts in 2022 compared to counterfactual tracts, representing a 9% decline in the base rate of out-migration (approximately 11%). Column (3) reveals a modest but significant decline of 1.7 in the average Equifax Risk Score for affected minority tracts when compared to unaffected tracts elsewhere in the country, representing a 0.3% decline in the base Equifax Risk Score.

Table A.8 presents summary statistics of consumers that moved in to the treated high-minority tracts. In 2020, around 10.8% of those that moved in to the treated high-minority tracts were coming from out of state, and in 2022, their share increased to 12.1%. For those that moved in from out of Nevada, the three states with the highest share of movers are California (30%), Florida (6%), and Texas (5%).

The results suggest that while demand increased in minority tracts, the average risk profile of residents in a particular area did not increase. This implies that the price and rent increases from censorship of the MLS Area labels can be attributed to a change in the perception of growth in and demand for minority neighborhoods, not the risk profile of residents in the neighborhood. In addition, the increase in movers from out-of-state indicates that the increase in demand for minority tracts is partly coming from outsiders that are less familiar with the change in neighborhood labels.

[28] Table A.7 presents summary statistics for the treated high-minority tracts in 2020 and 2022 in the FRBNY CCP/Equifax dataset.

VI. Conclusion

Racial disparities are present in housing markets for many reasons, including direct discrimination against racial minorities, imperfect access to information about available housing, and negative perceptions of minority neighborhoods. We examined the effects of labels and perception on real asset valuations using the censorship of a field in the MLS property search software of a major metropolitan area. Our results show that censoring the labels about asset location (i) steered migration of affluent individuals into historically recognized minority neighborhoods, (ii) widened the set of comparable property sales that appraisers used when valuing homes in predominately Black or Hispanic neighborhoods, and (iii) increased the prices of sales and leases of housing in minority neighborhoods by up to 10%–12%. The findings of this paper suggest that decoupling asset locations from labels when helping households find a place to live could help reduce racial differences in housing markets by changing the perception of future growth for areas previously constrained by the labels.

REFERENCES

Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder. 2021. "The effects of the 1930s HOLC "redlining" maps." *American Economic Journal: Economic Policy*, 13(4): 355–92.

Aaronson, Daniel, Jacob Faber, Daniel Hartley, Bhashkar Mazumder, and Patrick Sharkey. 2021. "The long-run effects of the 1930s HOLC "redlining" maps on place-based measures of economic opportunity and socioeconomic success." *Regional Science and Urban Economics*, 86: 103622.

Aaronson, Daniel, Joel Han, Daniel A Hartley, and Bhashkar Mazumder. 2023. "The Lasting Impact of Historical Residential Security Maps on Experienced Segregation."

Agarwal, Sumit, Hyun-Soo Choi, Jia He, and Tien Foo Sing. 2019. "Matching in housing markets: The role of ethnic social networks." *The Review of Financial Studies*, 32(10): 3958–4004.

Ambrose, Brent W, James Conklin, N Edward Coulson, Moussa Diop, and Luis A Lopez. 2021. "Do Appraiser and Borrower Race Affect Mortgage Collateral Valuation?" *Available at SSRN 3951587*.

Ambrose, Brent W, James N Conklin, and Luis A Lopez. 2021. "Does borrower and broker race affect the cost of mortgage credit?" *The Review of Financial Studies*, 34(2): 790–826.

Armona, Luis, Andreas Fuster, and Basit Zafar. 2019. "Home price expectations and behaviour: Evidence from a randomized information experiment." *The Review of Economic Studies*, 86(4): 1371–1410.

Avenancio-León, Carlos F, and Troup Howard. 2022. "The assessment gap: Racial inequalities in property taxation." *The Quarterly Journal of Economics*, 137(3): 1383–1434.

Bach, Laurent, Laurent E Calvet, and Paolo Sodini. 2020. "Rich pickings? Risk, return, and skill in household wealth." *American Economic Review*, 110(9): 2703–2747.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel. 2018. "The economic effects of social networks: Evidence from the housing market." *Journal of Political Economy*, 126(6): 2224–2276.

Bakkensen, Laura A, and Lint Barrage. 2022. "Going underwater? Flood risk belief heterogeneity and coastal home price dynamics." *The Review of Financial Studies*, 35(8): 3666–3709.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis. 2020. "Does climate change affect real estate prices? Only if you believe in it." *The Review of Financial Studies*, 33(3): 1256–1295.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace. 2022. "Consumer-lending discrimination in the FinTech era." *Journal of Financial Economics*, 143(1): 30–56.

Bayer, Patrick, Fernando Ferreira, and Stephen L Ross. 2018. "What drives racial and ethnic differences in high-cost mortgages? The role of high-risk lenders." *The Review of Financial Studies*, 31(1): 175–205.

Bottan, Nicolas L, and Ricardo Perez-Truglia. 2020. "Betting on the house: Subjective expectations and market choices." National Bureau of Economic Research.

Boyer, Brian H. 2011. "Style-related comovement: Fundamentals or labels?" *The Journal of Finance*, 66(1): 307–332.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 2016. "Understanding booms and busts in housing markets." *Journal of Political Economy*, 124(4): 1088–1147.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with a continuous treatment." *arXiv preprint arXiv:2107.02637*.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment." *American Economic Review*, 106(4): 855–902.

Crosignani, Matteo, and Hanh Le. 2023. "Stakeholders' Aversion to Inequality and Bank Lending to Under-Served Borrowers." *Working Paper*.

Diamond, Rebecca, GSB Stanford, and NBER William Diamond. 2024. "Racial Differences in the Total Rate of Return on Owner-Occupied Housing."

DiPasquale, Denise, and William C Wheaton. 1992. "The markets for real estate assets and space: A conceptual framework." *Real Estate Economics*, 20(2): 181–198.

D'Lima, Walter, Luis A Lopez, and Archana Pradhan. 2022. "COVID-19 and housing market effects: Evidence from US shutdown orders." *Real Estate Economics*, 50(2): 303–339.

Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri. 2020. "Heterogeneity and persistence in returns to wealth." *Econometrica*, 88(1): 115–170.

Fishback, Price. 2014. "Panel Discussion on Saving the Neighborhood: Part III." *Arizona Law Review, available at http://arizonalawreview. org/fishback.*

Fishback, Price V, Jessica LaVoice, Allison Shertzer, and Randall Walsh. 2023. "The HOLC maps: How race And poverty influenced real estate professionals' evaluation of lending risk in the 1930s." *Journal of Economic History.* Forthcoming.

Frame, W Scott, Ruidi Huang, Erik J Mayer, and Adi Sunderam. 2021. "Minority loan officers and minorities' access to mortgage credit." *SMU Cox School of Business Research Paper Forthcoming.*

Freddie Mac. 2022. "Racial & Ethnic Valuation Gaps in Home Purchase Appraisals - A Modeling Approach." *Freddie Mac Economic & Housing Research Note.*

Giacoletti, Marco, Rawley Z Heimer, and Edison Yu. 2021. *Using high-frequency evaluations to estimate discrimination: Evidence from mortgage loan officers.* Research Department, Federal Reserve Bank of Philadelphia.

Glaeser, Edward L, and Charles G Nathanson. 2017. "An extrapolative model of house price dynamics." *Journal of Financial Economics*, 126(1): 147–170.

Goetzmann, William N, Christophe Spaenjers, and Stijn Van Nieuwerburgh. 2021. "Real and private-value assets." *The Review of Financial Studies*, 34(8): 3497–3526.

Goldsmith-Pinkham, Paul, Matthew T Gustafson, Ryan C Lewis, and Michael Schwert. 2023. "Sea-level rise exposure and municipal bond yields." *The Review of Financial Studies*, 36(11): 4588–4635.

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh. 2022. "Flattening the curve: pandemic-induced revaluation of urban real estate." *Journal of Financial Economics*, 146(2): 594–636.

Hanson, Andrew, and Zackary Hawley. 2023. "Restricted access: Real estate agent response to client race, ethnicity, gender, and side of market." *Real Estate Economics.*

Hartley, Daniel A, and Jonathan Rose. 2023. "Blockbusting and the Challenges Faced by Black Families in Building Wealth through Housing in the Postwar United States."

Hillier, Amy E. 2003. "Redlining and the home owners' loan corporation." *Journal of Urban History*, 29(4): 394–420.

Holmes, Andrew, and Paul Horvitz. 1994. "Mortgage redlining: Race, risk, and demand." *The Journal of Finance*, 49(1): 81–99.

Howell, Junia, and Elizabeth Korver-Glenn. 2018. "Neighborhoods, Race, and the Twenty-first-century Housing Appraisal Industry." *Sociology of Race and Ethnicity*, 4(4): 473–490.

Howell, Junia, and Elizabeth Korver-Glenn. 2020. "The increasing effect of neighborhood racial composition on housing values, 1980–2015." *Social Problems*.

Jackson, Kenneth T. 1980. "Race, Ethnicity, and Real Estate Appraisal: The Home Owners Loan Corporation and the Federal Housing Administration." *Journal of Urban History*, 6(4): 419–452.

Kuchler, Theresa, and Basit Zafar. 2019. "Personal experiences and expectations about aggregate outcomes." *The Journal of Finance*, 74(5): 2491–2542.

Kuhn, Moritz, Moritz Schularick, and Ulrike I Steins. 2020. "Income and wealth inequality in America, 1949–2016." *Journal of Political Economy*, 128(9): 3469–3519.

Liu, Haoyang, and Christopher Palmer. 2021. "Are stated expectations actual beliefs? New evidence for the beliefs channel of investment demand." National Bureau of Economic Research.

Lopez, Luis A. 2021. "Asymmetric information and personal affiliations in brokered housing transactions." *Real Estate Economics*, 49(2): 459–492.

Lopez, Luis A. 2022. "Is there a Principal-Agency Problem with Real Estate Agents in Rental Markets?" *The Journal of Real Estate Finance and Economics*, 1–41.

Lopez, Luis A, and Jiro Yoshida. 2022. "Estimating housing rent depreciation for inflation adjustments." *Regional Science and Urban Economics*, 95: 103733.

Lopez, Luis A, Shawn J McCoy, and Vivek Sah. 2022. "Steering consumers to lenders in residential real estate markets." *Real Estate Economics*, 50(6): 1596–1641.

Lovenheim, Michael F, and Kevin J Mumford. 2013. "Do family wealth shocks affect fertility choices? Evidence from the housing market." *Review of Economics and Statistics*, 95(2): 464–475.

Markley, Scott. 2023. "Federal 'redlining'maps: A critical reappraisal." *Urban Studies*, 00420980231182336.

Nagaraj, Abhishek, and Scott Stern. 2020. "The economics of maps." *Journal of Economic Perspectives*, 34(1): 196–221.

National Association of Realtors. 2020. "NAR President Charlie Oppler Apologizes for Past Policies that Contributed to Racial Inequality." https://www.nar.realtor/newsroom/nar-president-charlie-oppler-apologizes-for-past-policies-that-contributed-to-racial-inequality.

Ondrich, J., S. Ross, and J. Yinger. 2003. "Now you see it, now you don't: Why do real estate agents withhold available houses from black customers?" *Review of Economics and Statistics*, 85(4): 854–873.

Perry, Andre M., Jonathan Rothwell, and David Harshbarger. 2018. "The devaluation of assets in Black neighborhoods: The case of residential property." *Brookings*, November: 1–28.

Piazzesi, Monika, and Martin Schneider. 2009. "Momentum traders in the housing market: Survey evidence and a search model." *American Economic Review*, 99(2): 406–411.

Pinto, Edward, and Tobias Peter. 2021. "How common is appraiser racial bias?" American Enterprise Institute Housing Center Working Report. https://www.aei.org/how-common-is-appraiser-racial-bias/.

Pinto, Edward, and Tobias Peter. 2022. "How Common Is Appraiser Racial Bias—an Update." American Enterprise Institute Housing Center Working Report. https://www.aei.org/research-products/report/how-common-is-appraiser-racial-bias-an-update/.

Pinto, Edward, and Tobias Peter. 2023. "Exploring alternative explanations for appraisal under-valuations: A critique of FHFA, Brookings, and Freddie Mac reports on racial bias." American Enterprise Institute Housing Center Working Report. https://www.aei.org/wp-content/uploads/2023/02/Exploring-alternative-explanations-for-appraisal-under-valuations-A-critique-of-FHFA-Brookings-and-Freddie-Mac-reports-on-racial.pdf?x85095.

Rambachan, Ashesh, and Jonathan Roth. 2023. "A more credible approach to parallel trends." *Review of Economic Studies*, rdad018.

Redlining Discrimination in Residential Mortgage Loans, Robert "Bob"' Price Political Papers. 1959-1988. Special Collections and Archives, University Libraries, University of Nevada, Las Vegas. Las Vegas, Nevada. MS-00246, Box 04. `https://special.library.unlv.edu/sites/default/files/finding-aids/MS-00246.pdf`.

Tootell, Geoffrey MB. 1996. "Redlining in Boston: Do mortgage lenders discriminate against neighborhoods?" *The Quarterly Journal of Economics*, 111(4): 1049–1079.

Van Nieuwerburgh, Stijn. 2023. "The remote work revolution: Impact on real estate values and the urban environment: 2023 AREUEA Presidential Address." *Real Estate Economics*, 51(1): 7–48.

Williamson, Jake, and Mark Palim. 2022. "Appraising the Appraisal." *Fannie Mae Working Paper*.

DATA REFERENCES

Clark County Assessor Office (2019). AO Parcel XY Table Layout (pcl_ll_x). https://secureftp.co.clark.nv.us/ (accessed April 15, 2019).

Clark County Assessor Office (2019). Residential Extract Files (AORES). https://secureftp.co.clark.nv.us/ (accessed April 15, 2019).

Clark County Assessor Office (2019). Secured Tax Roll Master File (AOEXTRACT). https://secureftp.co.clark.nv.us/ (accessed April 15, 2019).

FRBNY Consumer Credit Panel/Equifax Data (CCP) (2022). Equifax credit reports, 2020-2022. https://www.newyorkfed.org/research/staff_reports/sr479.

Federal Housing Finance Agency Uniform Appraisal Dataset Aggregate Statistics (2023) Census Tracts. https://www.fhfa.gov/DataTools/Pages/UAD-Dashboards.aspx (accessed June 27, 2023).

Home Mortgage Disclosure Act (2018). Public HMDA - LAR Data. https://ffiec.cfpb.gov/documentation/api/data-browser/ (accessed Jan. 6, 2022)

Las Vegas Realtors Multiple Listing Service (2022). CoreLogic MLS Matrix, Residential Search Data, 2006-2022. https://las.mlsmatrix.com/.

Las Vegas Realtors Multiple Listing Service (2022). CoreLogic MLS Matrix, Residential Rental Search Data, 2008-2022. https://las.mlsmatrix.com/.

U.S. Census Bureau. (2023). American Community Survey: 5-Year Estimates, 2009-2013. https://api.census.gov/data/2013/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau. (2023). American Community Survey: 5-Year Estimates, 2010-2014. https://api.census.gov/data/2014/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau. (2023). American Community Survey: 5-Year Estimates, 2011-2015. https://api.census.gov/data/2015/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau. (2023). American Community Survey: 5-Year Estimates, 2012-2016. https://api.census.gov/data/2016/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau. (2023). American Community Survey: 5-Year Estimates, 2013-2017. https://api.census.gov/data/2017/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau. (2023). American Community Survey: 5-Year Estimates, 2014-2018. https://api.census.gov/data/2018/acs/acs5 (accessed January 16, 2023).

U.S. Census Bureau. (2023). American Community Survey: 5-Year Estimates, 2015-2019. `https://api.census.gov/data/2019/acs/acs5` (accessed January 16, 2023).

Table I: FHFA Appraisal, HMDA, and ACS Tract Characteristics

Panel A: Before Matching	Treated?				
	No	Yes	Difference	t-stat	d-stat
Outcome Variables					
Appraised Mean Value ($1,000s)	409.35	354.56	-54.79	-2.89	-0.14
Avg. Distance of Comp's (miles)	1.96	0.58	-1.38	-10.06	-0.50
Share Common Tract	0.53	0.58	0.05	4.86	0.24
Purchase Appraisals Count	45.92	50.84	4.92	2.86	0.15
Control Variables					
ln(Tract Median Family Income)	11.22	11.08	-0.14	-6.53	-0.32
ln(Tract Median Gross Rent)	6.95	7.07	0.12	6.15	0.31
Tract Hispanic Share	0.15	0.31	0.16	16.74	0.83
Tract Black Share	0.10	0.10	0.00	-0.22	-0.01
Tract API Share	0.05	0.09	0.04	9.39	0.47
Tract Vacancy Rate	0.11	0.12	0.01	2.10	0.10
Tract Renters-to-Owners Ratio	0.73	1.29	0.56	8.33	0.41
Conv. Mortgage Rejection Rate	0.08	0.09	0.00	0.67	0.03
FHA Mortgage Rejection Rate	0.11	0.09	-0.02	-2.68	-0.13
Pre-Trend Growth Rate	0.06	0.10	0.04	18.16	0.94
Observations (unique tracts)	48,407	410			

Panel B: After Matching	Treated?				
Variables	No	Yes	Difference	t-stat	d-stat
Outcome Variables					
Appraised Mean Value ($1,000s)	538.47	366.72	-171.75	-7.18	-0.39
Avg. Distance of Comp's (miles)	1.07	0.55	-0.52	-5.93	-0.32
Share Common Tract	0.55	0.59	0.05	4.72	0.26
Purchase Appraisals Count	42.58	52.15	9.57	4.94	0.27
Control Variables					
ln(Tract Median Family Income)	11.15	11.13	-0.02	-1.04	-0.06
ln(Tract Median Gross Rent)	7.14	7.10	-0.04	-1.95	-0.11
Tract Hispanic Share	0.30	0.29	0.00	-0.11	-0.01
Tract Black Share	0.10	0.10	0.00	-0.01	0.00
Tract API Share	0.10	0.09	0.00	-0.06	0.00
Tract Vacancy Rate	0.11	0.11	0.00	0.40	0.02
Tract Renters-to-Owners Ratio	0.93	0.99	0.06	1.02	0.06
Conv. Mortgage Rejection Rate	0.08	0.08	0.00	-0.15	-0.01
FHA Mortgage Rejection Rate	0.09	0.09	0.00	-0.30	-0.02
Pre-Trend Growth Rate	0.10	0.10	0.01	2.32	0.13
Observations (unique tracts)	3,286	373			

This table reports summary statistics for the treated and control census tracts including the average value, mean difference, t-test statistic, and Cohen's d-statistic. Treated census tracts are in Clark County, NV, while control tracts are elsewhere in the nation. Panel A presents the pre-matching statistics, whereas Panel B presents the post-matching statistics.

Table II: MLS Property Characteristics

	Sales		Leases	
Variables	Mean	SD	Mean	SD
Close Price ($)	281,428	153,475	1,464	670
Living Area Square Feet	1,852	751	1,694	703
Lot Size Square Feet	5,508	4,468	3,855	3,445
Structure's Age	21.12	12.90	18.29	10.38
Bedrooms	3.18	0.91	2.93	0.95
Bathrooms	2.60	0.74	2.51	0.74
Fireplaces	0.53	0.62	0.43	0.57
Garage Car Spaces	1.83	0.91	1.59	0.93
Private Pool	0.19	.	0.09	.
Private Spa	0.13	.	0.06	.
Property Type: Single-family	0.80	.	0.67	.
Property Type: Condominium	0.12	.	0.24	.
Property Type: 2-4 Unit	0.08	.	0.09	.
MLS Area Censored	0.10	.	0.09	.
Observations	357,980		258,341	

This table reports the mean and standard deviation of structural characteristics among sales and leases. The standard deviation is omitted for binary variables. The sample covers Clark County, NV from January 2013 to December 2022.

Table III: Neighborhood Labeling Effects on Appraisal Practices

	(1) ln(Value)	(2) ln(Distance)	(3) Same Tract	(4) Count
Post × Tract Minority Share	-0.013	0.011	-0.009	14.979***
	(-0.905)	(1.332)	(-1.423)	(8.967)
Post × Treatment	0.040***	0.005	-0.018***	-16.267***
	(4.698)	(0.943)	(-5.360)	(-14.061)
Post × Treatment × Tract Minority Share	0.072***	0.024***	-0.011*	15.522***
	(4.925)	(2.914)	(-1.894)	(9.292)
Observations	7,132	7,132	7,132	5,730
Adjusted R-squared	0.984	0.971	0.880	0.781
Singletons	93	93	93	706
Tract FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

This table reports OLS estimates of the effect of removing MLS labels using tract-level observations on appraisal outcomes from the FHFA Appraisal Data. Post is 1 if the year is 2022, and 0 if the year is 2020. Tract Minority Share is the tract share of minority households as of the 2018 ACS 5-year estimates. Treatment is 1 if the tract is in Clark County, NV, and 0 if the observation is of a match tract outside of the treatment area. The control tracts are matched using pre-treatment characteritics including the tract median family income, tract median gross rent, tract hispanic share, tract black share, tract asian and pacific islander share, tract vacancy share, tract renters-to-owners ratio, conventional mortgage rejection rate, FHA mortgage rejection rate, and the 5-year pre-trend growth rate. t-Statistics using robust standard errors clustered by county are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table IV: Neighborhood Labeling Effects on Rents and Sales

	(1) ln(Price) Sales	(2) ln(Price) Sales	(3) ln(Price) Sales	(4) ln(Rent) Leases	(5) ln(Rent) Leases	(6) ln(Rent) Leases
Treated	-0.158***	-0.041***	-0.039***	-0.024***	-0.033***	-0.031**
	(-26.848)	(-3.436)	(-3.209)	(-4.176)	(-2.668)	(-2.487)
Minority Share × Treated	0.332***	0.108***	0.103***	0.104***	0.120***	0.117***
	(40.438)	(4.720)	(4.486)	(14.509)	(5.500)	(5.353)
Observations	171,336	171,043	170,288	203,080	202,888	200,753
Adjusted R-squared	0.944	0.953	0.953	0.964	0.966	0.967
Singletons	186,667	186,960	186,636	56,402	56,594	56,621
Tract Characteristics FE			✓			✓
Parcel FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓			✓		
ZIP-Year-Quarter FE		✓	✓		✓	✓

This table reports OLS estimates of the effect of removing MLS labels on the natural log of price for sold properties in columns (1) to (3) and leased properties in columns (4) to (6). The sample consists of transactions from 2013 to 2022 in Clark County, NV. *Treated* is an indicator function that equals one if the MLS Area was excluded from the listing sheet; it is zero otherwise. *Minority Share* is the proportion of individuals within the same MLS Area that are not non-Hispanic White as of the 2018 ACS, 5 year-estimates. Tract characteristics include log tract median family income, log tract median gross rent, tract capitalization rate, tract vacancy share, tract Hispanic share, tract Asian and Pacific Islander (API) share, tract Black share, and tract renters-to-owners ratio. The tract characteristics are 5-year ACS estimates that are lagged by three years. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table V: Neighborhood Labeling Effects at Area Boundaries

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Price)	ln(Price)	ln(Price)	ln(Rent)	ln(Rent)	ln(Rent)
Transaction:	Sales	Sales	Sales	Leases	Leases	Leases
Location:	Center	Periphery1	Periphery2	Center	Periphery1	Periphery2
Treated	-0.046	-0.040**	-0.041**	0.022	-0.007	-0.059***
	(-1.061)	(-2.327)	(-2.076)	(0.417)	(-0.352)	(-2.916)
Minority Share × Treated	0.096	0.107***	0.117***	0.014	0.063*	0.190***
	(1.107)	(3.269)	(2.997)	(0.149)	(1.860)	(5.162)
Observations	18,788	96,346	54,476	19,650	117,400	63,149
Adjusted R-squared	0.959	0.952	0.955	0.968	0.966	0.969
Singletons	21,419	109,139	56,756	6,429	32,761	17,985
Tract Characteristics	✓	✓	✓	✓	✓	✓
Parcel FE	✓	✓	✓	✓	✓	✓
ZIP-Year-Quarter FE	✓	✓	✓	✓	✓	✓

This table reports OLS estimates of the effect of removing MLS labels on the natural log of price for sold properties in columns (1) to (3) and leased properties in columns (4) to (6). The sample consists of transactions from 2013 to 2022 in Clark County, NV. *Treated* is an indicator function that equals one if the MLS Area was excluded from the listing sheet; it is zero otherwise. *Minority Share* is the proportion of individuals within the same MLS Area that are not non-Hispanic White as of the 2018 ACS, 5 year-estimates. Tract characteristics include log tract median family income, log tract median gross rent, tract capitalization rate, tract vacancy share, tract Hispanic share, tract Asian and Pacific Islander (API) share, tract Black share, and tract renters-to-owners ratio. The tract characteristics are 5-year ACS estimates that are lagged by three years. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table VI: Neighborhood Labeling Effects on Rents and Sales by Area Cohorts

	(1) ln(Price) Sales	(2) ln(Rent) Leases
Treated	0.002	0.016***
	(0.481)	(2.953)
1[Minority Share between 50% and 75%] × Treated	0.018***	0.023***
	(3.137)	(4.469)
1[Minority Share between 75% and 100%] × Treated	0.099***	0.060***
	(5.946)	(4.006)
Observations	170,288	200,753
Adjusted R-squared	0.953	0.967
Singletons	186,636	56,621
Tract Characteristics	✓	✓
Parcel FE	✓	✓
ZIP-Year-Quarter FE	✓	✓

This table reports OLS estimates of the effect of removing MLS labels by area cohort on the natural log of price for sold properties in column (1) and leased properties in column (2). The sample consists of transactions from 2013 to 2022 in Clark County, NV. *Treated* is an indicator function that equals one if the MLS Area was excluded from the listing sheet; it is zero otherwise. *Minority Share* is the proportion of individuals within the same MLS Area that are not non-Hispanic White as of the 2018 ACS, 5 year-estimates. Tract characteristics include log tract median family income, log tract median gross rent, tract capitalization rate, tract vacancy share, tract Hispanic share, tract Asian and Pacific Islander (API) share, tract Black share, and tract renters-to-owners ratio. The tract characteristics are 5-year ACS estimates that are lagged by three years. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table VII: Neighborhood Labeling Effects on Rents and Sales in Underserved Areas

	(1) ln(Price) Sales	(2) ln(Price) Sales	(3) ln(Price) Sales	(4) ln(Rent) Leases	(5) ln(Rent) Leases	(6) ln(Rent) Leases
Treated	0.016***	0.016***	0.015***	0.031***	0.030***	0.030***
	(4.176)	(4.198)	(4.026)	(7.538)	(7.425)	(7.409)
Family Income^z × Treated	-0.097***			-0.077***		
	(-7.003)			(-6.237)		
Vacancy Rate^z × Treated		0.016**			0.004	
		(2.345)			(0.626)	
Rent-to-Own Ratio^z × Treated			0.010***			0.003***
			(6.058)			(2.603)
Observations	171,043	171,043	171,043	202,888	202,888	202,888
Adjusted R-squared	0.953	0.953	0.953	0.966	0.966	0.966
Singletons	186,960	186,960	186,960	56,594	56,594	56,594
Parcel FE	✓	✓	✓	✓	✓	✓
ZIP-Year-Quarter FE	✓	✓	✓	✓	✓	✓

This table reports OLS estimates of the effect of removing MLS labels by neighborhood on the natural log of price for sold properties in columns (1) to (3) and leased properties in columns (4) to (6). The censorship indicator is interacted with various measures of perceived area quality including the median family income, vacancy rate, and rent-to-owner (RO) ratio. The z superscript indicates that the variable was standardized into z-scores. The sample consists of transactions from 2013 to 2022 in Clark County, NV. *Treated* is an indicator function that equals one if the MLS Area was excluded from the listing sheet; it is zero otherwise. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table VIII: Neighborhood Labeling Effects by Demographics

	(1) Sales	(2) Leases
Treated	-0.036***	0.009
	(-5.370)	(1.376)
Tract Hispanic Share as of 2018 × Treated	0.173***	0.111***
	(11.054)	(8.388)
Tract Black Share as of 2018 × Treated	0.233***	0.074***
	(9.162)	(3.797)
Tract API Share as of 2018 × Treated	-0.158***	-0.088***
	(-6.340)	(-4.365)
Observations	170,288	200,753
Adjusted R-squared	0.953	0.967
Singletons	186,636	56,621
Tract Characteristics*	✓	✓
Parcel FE	✓	✓
ZIP-Year-Quarter FE	✓	✓

This table reports OLS estimates of the effect of removing MLS labels by the tract Hispanic, Black, or API share on the log price for purchase contracts in column (1) and rental contracts in column (2). The sample consists of sales transactions from 2013 to 2022 in Clark County, NV. *Treated* is an indicator function that equals one if the MLS Area was excluded from the listing sheet; it is zero otherwise. *Tract Hispanic Share as of 2018* is the proportion of individuals in the census tract that are Hispanic as of the 2018 ACS, 5 year-estimates. *Tract Black Share as of 2018* is the proportion of individuals in the census tract that are non-Hispanic Black as of the 2018 ACS, 5 year-estimates. *Tract API Share as of 2018* is the proportion of individuals in the census tract that are non-Hispanic Asians or Pacific Islanders as of the 2018 ACS, 5 year-estimates. Tract characteristics* include log tract median family income, log tract median gross rent, tract capitalization rate, tract vacancy share, and tract renters-to-owners ratio. The tract characteristics are 5-year ACS estimates that are lagged by three years. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table IX: Neighborhood Labeling Effects on Cap Rate

	(1) Cap Rate
Treated	0.008***
	(5.605)
Minority Share × Treated	-0.016***
	(-6.049)
Observations	170,288
Adjusted R-squared	0.834
Singletons	186,636
Parcel FE	✓
Tract Characteristics	✓
ZIP-Year-Quarter FE	✓

This table reports OLS estimates of the effect of removing MLS labels by each area's minority share on the cap rate. The sample consists of sales transactions from 2013 to 2022 in Clark County, NV. The *Cap Rate* is calculated as the imputed annual rental rate divided by the observed close price. The imputed rent is obtained from a hedonic rent model using a sample of leases from 2008Q1-2022Q4. *Treated* is an indicator function that equals one if the MLS Area was excluded from the listing sheet; it is zero otherwise. *Minority Share* is the proportion of individuals within the same MLS Area that are not non-Hispanic White as of the 2018 ACS, 5 year-estimates. Tract characteristics include log tract median family income, log tract median gross rent, tract capitalization rate, tract vacancy share, tract Hispanic share, tract Asian and Pacific Islander (API) share, tract Black share, and tract renters-to-owners ratio. The tract characteristics are 5-year ACS estimates that are lagged by three years. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table X: Neighborhood Labeling Effects on Migration Patterns

	(1) Move-In	(2) Move-Out	(3) Equifax Risk Score
Post × Tract Minority Share	0.004	0.00	1.717***
	(0.935)	(1.095)	(2.836)
Post × Treatment	-0.020***	-0.040***	0.657*
	(-9.062)	(-15.647)	(1.935)
Post × Treatment × Tract Minority Share	0.028***	-0.011***	-1.721***
	(5.976)	(-2.962)	(-2.843)
Tract FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	7,318	7,318	7,318
Adjusted R-squared	0.714	0.673	0.980

This table reports the results of a triple-difference model with the three differences being: (i) Las Vegas census tracts vs. matched control tracts, (ii) observation before and after the MLS Area code censorship (from 2020 to 2022), and (iii) minority census tracts vs non-minority census tracts. The dependent variable in column 1 is the share of CCP consumers in a census tract that moved-in and in column 2 it is those that moved-out. More specifically, if a customer has a registered change in their FIPS code in the last (next) 18, 12, and 6 months, they are marked as an in-migrants (out-migrants) "mover". We limit the age of the consumers in the data to be between 18 to 95. Columns 3 measures the average Equifax Risk Score at the census tract level. t-Statistics using robust standard errors clustered by county are reported in parentheses. Equifax consumer credit reports and Equifax data assets do not contain information about consumer's race or gender. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Source: FRBNY Consumer Credit Panel (CCP)/Equifax dataset.

Table XI: Neighborhood Labeling Effects on Racial Composition

	(1)	(2)	(3)	(4)
Panel A - Racial Composition	non-Hispanic White	non-Hispanic Black	non-Hispanic Asians	Hispanic
Post × Tract Minority Share	0.044***	-0.007**	0.006	-0.038***
	(6.434)	(-2.309)	(0.985)	(-5.520)
Post × Treatment	-0.058***	-0.003**	0.036***	0.020***
	(-13.499)	(-2.027)	(11.211)	(7.556)
Post × Treatment × Tract Minority Share	0.068***	0.009***	-0.014**	-0.048***
	(9.892)	(2.997)	(-2.292)	(-7.026)
Observations	7,312	7,312	7,312	7,312
Adjusted R-squared	0.913	0.808	0.892	0.898
Panel B - Log Income	non-Hispanic White	non-Hispanic Black	non-Hispanic Asians	Hispanic
Post × Tract Minority Share	-0.176***	-0.095***	-0.160**	-0.173***
	(-3.315)	(-2.770)	(-2.200)	(-2.813)
Post × Treatment	-0.116***	-0.093***	-0.200***	-0.267***
	(-3.395)	(-6.753)	(-4.809)	(-6.476)
Post × Treatment × Tract Minority Share	0.389***	0.316***	0.512***	0.513***
	(7.338)	(9.167)	(7.020)	(8.349)
Observations	6,046	6,908	3,892	5,224
Adjusted R-squared	0.479	0.698	0.361	0.466
Panel C - Age	non-Hispanic White	non-Hispanic Black	non-Hispanic Asians	Hispanic
Post × Tract Minority Share	0.454	-0.228	-0.046	-0.506
	(0.695)	(-0.517)	(-0.041)	(-0.663)
Post × Treatment	-2.818***	-2.558***	-4.421***	-2.593***
	(-6.504)	(-13.301)	(-6.621)	(-5.502)
Post × Treatment × Tract Minority Share	3.310***	4.748***	3.576***	4.659***
	(5.067)	(10.771)	(3.221)	(6.108)
Observations	6,046	6,908	3,892	5,224
Adjusted R-squared	0.236	0.514	0.189	0.204

This table reports the results of a triple-difference model with the three differences being: (i) Las Vegas census tracts vs. matched control tracts, (ii) observation before and after the MLS Area code censorship, and (iii) minority census tracts vs non-minority census tracts. We test for differences in migration patterns by the racial composition of mortgage applicants from 2020 to 2022. Panel A presents the racial composition of the neighborhoods as the share of mortgage applicants at the tract-level that are non-Hispanic White in column 1, non-Hispanic Black in column 2, non-Hispanic Asians in column 3, and Hispanic in column 4. Panel B and C present the average log income and age of purchase mortgage applicants by racial group aggregated to the tract-level, respectively. Panels B and C have fewer observations than Panel A because not all racial groups apply for mortgages in all the tracts every year. All specifications include census tracts and year fixed effects. t-Statistics using robust standard errors clustered by county are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Source: Home Mortgage Disclosure Act (HMDA) database.

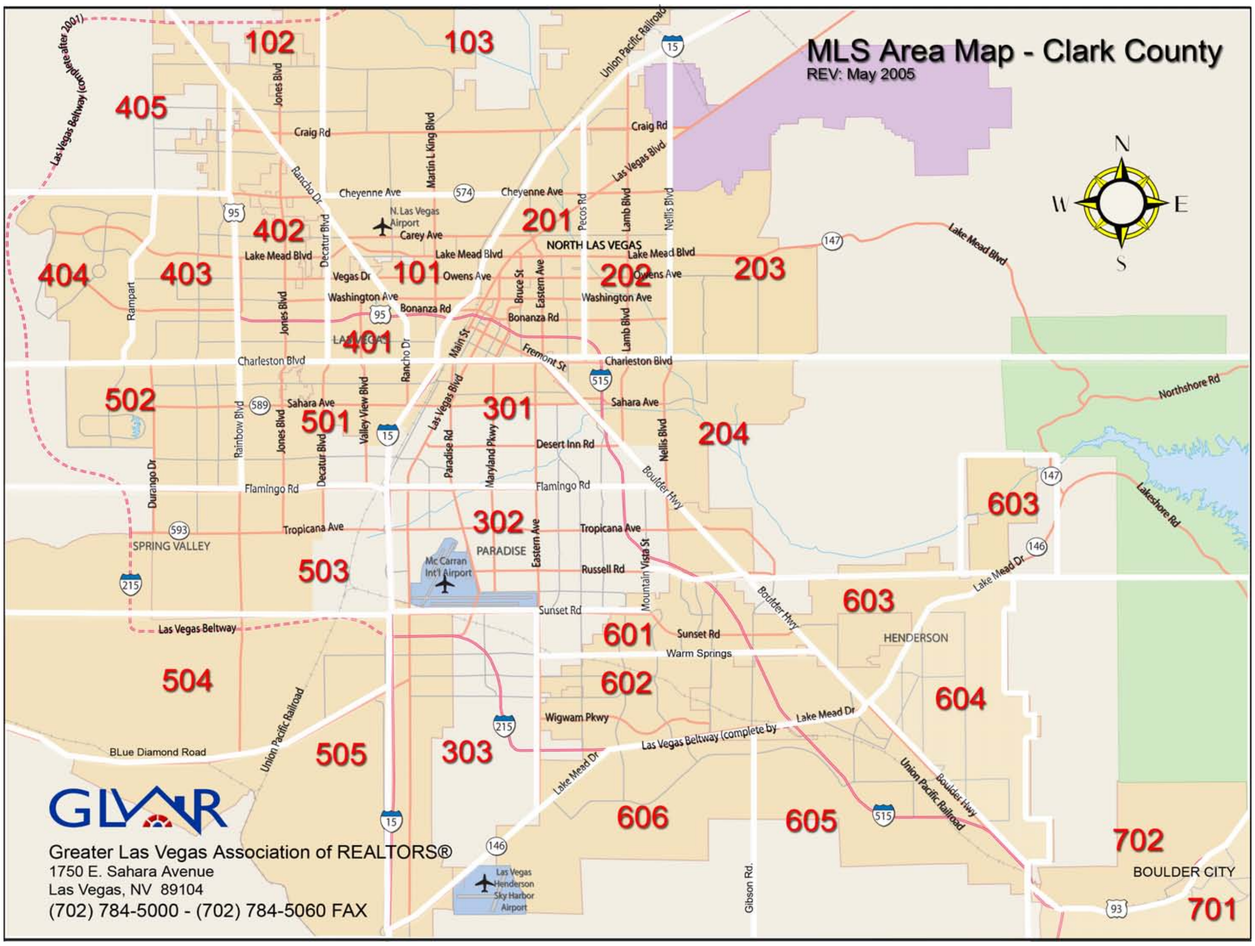
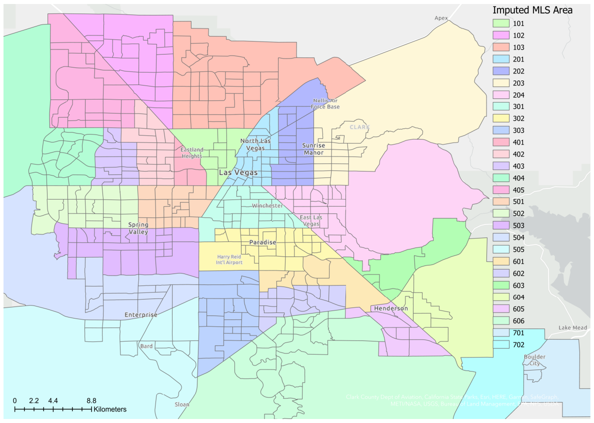
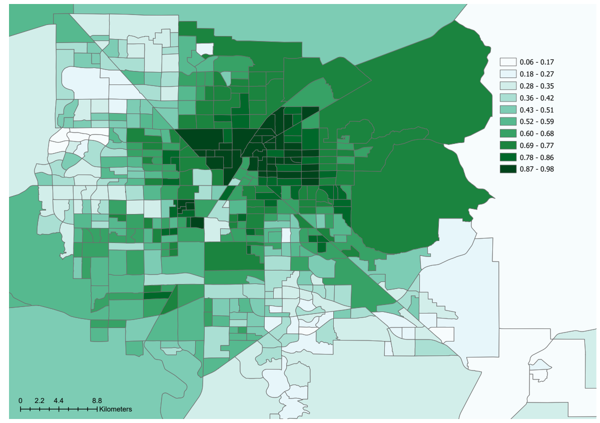


Figure 1. Realtor MLS Area Map

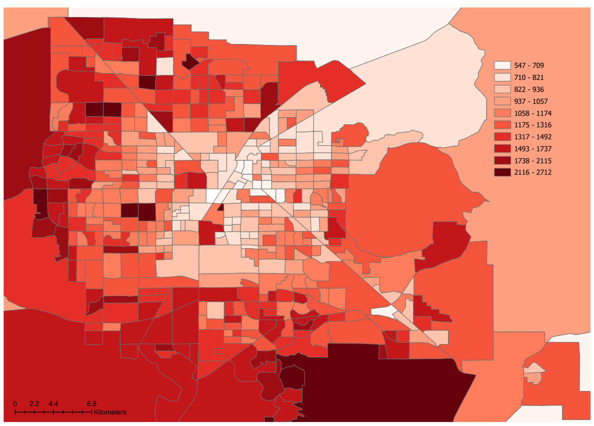
This figure is a map of the MLS Areas provided by the Las Vegas Realtors (formerly the Greater Las Vegas Association of Realtors).



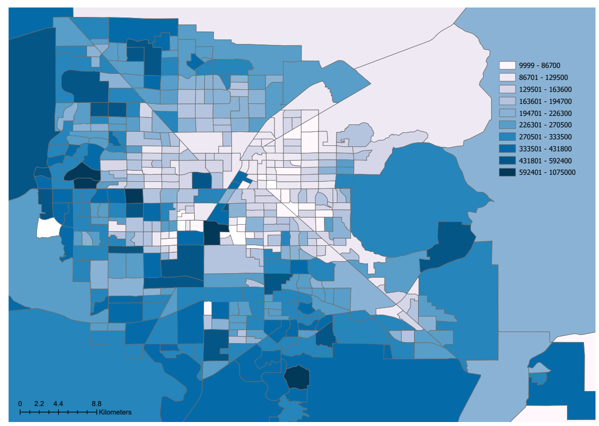
(a) MLS Areas



(b) Minority Share



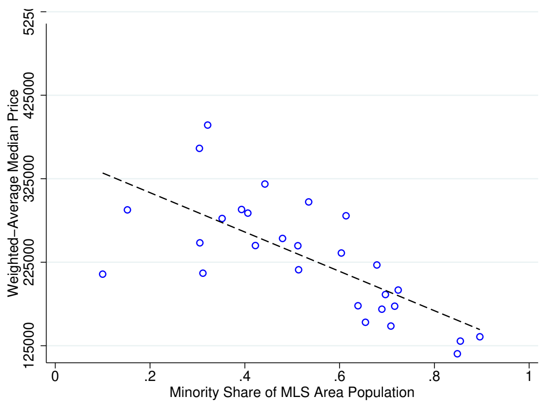
(c) Rental Rates



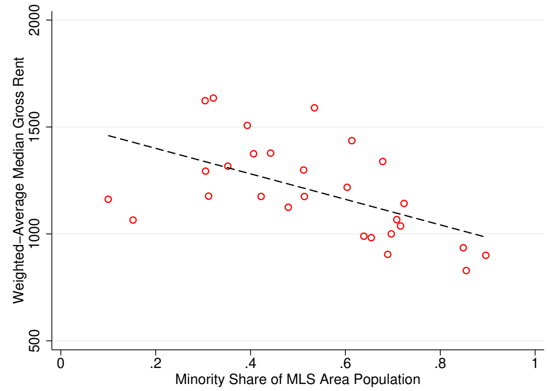
(d) Property Values

Figure 2. Maps of Clark County, NV

Panel (a) maps the mode MLS Area by census tract. Panel (b) reports the share of minorities, measured as 1 minus the population share of non-Hispanic Whites from the 2018 ACS 5-year estimate by census tract. Panel (c) plots the median home price values from the 2018 ACS 5-year estimate by census tract. Panel (d) plots the monthly rental rate from the 2018 ACS 5-year estimate by census tract. This figure uses the 2010 TIGER/Line® Shapefiles for Clark County, NV from the U.S. Census Bureau.



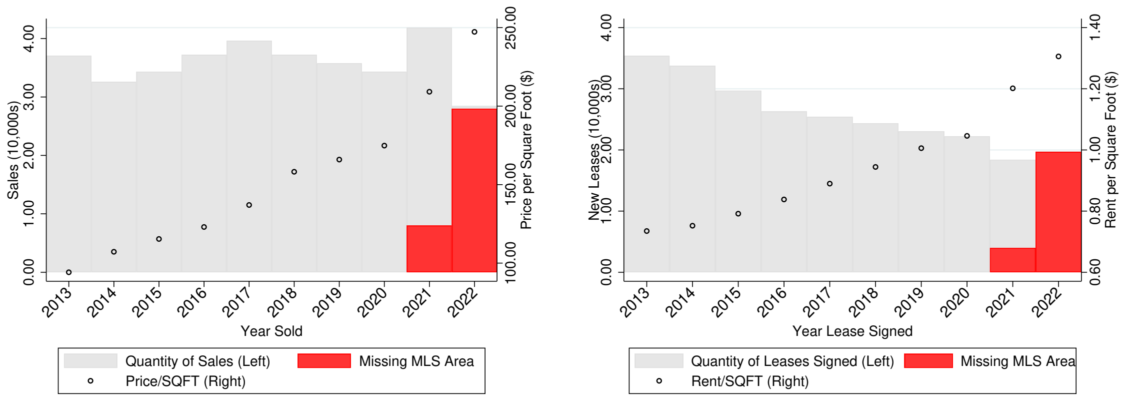
(a) Sales Price



(b) Rental Rate

Figure 3. Price, Rent, and Minority Share at the MLS Area Level

This figure plots the sales price and minority share coordinate point for each MLS Area in Panel A, and the rental rate and minority share coordinate point for each MLS Area in Panel B. The price, rent, and minority share statistics are from the 2014-2018 American Community Survey, 5-year estimates. The dashed line in black is the linear fit between price or rent and minority share. The price is measured as the population-weighted-average median price across census tracts within each MLS Area. The rent and minority share are calculated at the MLS Area level in a similar way.

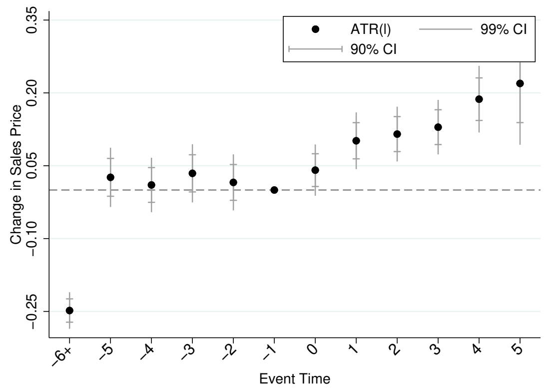


(a) Sales

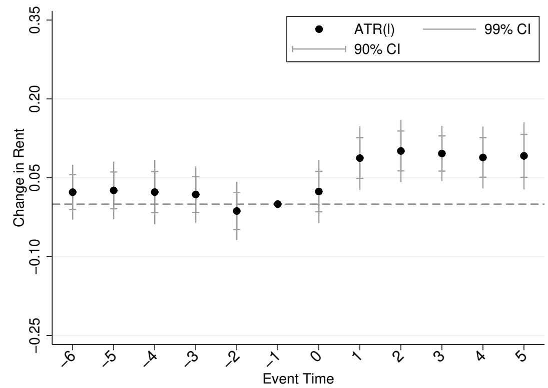
(b) Rents

Figure 4. Las Vegas Metro Market Trends

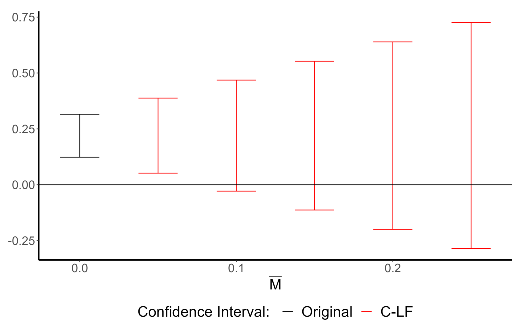
This figure reports the number of sales and price per square foot (winsorized, 1% tails) in Panel A, and the number of leases and rent per square foot (winsorized, 1% tails) in Panel B. The red bars indicate the number of sales or leases that did not report the Area when listed in the MLS.



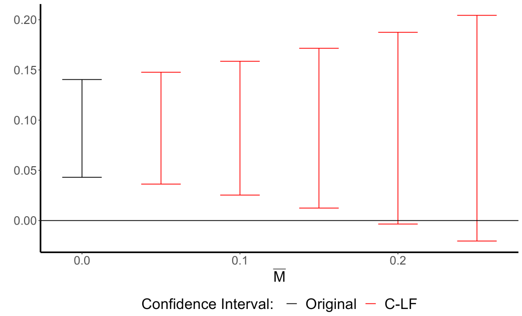
(a) Sales



(b) Leases



(c) Sales



(d) Leases

Figure 5. Average Treatment Response of Minority Neighborhoods

This figure illustrates the average treatment response of minority neighborhoods to the removal of the MLS Area field over time by quarterly increments from 2013Q1 to 2022Q4 for sales in Panel A and leases in Panel B. The event time at zero represents listings in 2021Q3, the first quarter when the MLS Area field was removed. Panels C and D provide an analysis of the potential violation of the parallel trends assumption bounding 95% confidence interval sets, per Rambachan and Roth (2023). The confidence intervals in black are from the event time $l = 5$, and the confidence intervals in red are the conditional-least favorable by $\overline{M}$ times the max pre-treatment trend.

Appendix

Table A.1: MLS Area Demographics

MLS Area	Family Income ($)	Vacancy	Renter-to-Owner	Minority Share
101	39,633	.15	2.04	.90
102	92,157	.08	.37	.39
103	69,911	.07	.67	.68
201	39,082	.18	8.02	.85
202	40,379	.14	3.08	.85
203	58,238	.1	.77	.72
204	53,322	.13	1.25	.71
301	46,363	.32	13.76	.69
302	48,730	.14	16.22	.64
303	74,526	.14	2.05	.51
401	55,325	.12	1.01	.72
402	52,085	.1	1.56	.65
403	68,004	.13	1.26	.51
404	10,151	.11	.42	.32
405	88,367	.09	.62	.41
501	48,749	.11	3.93	.70
502	78,106	.13	1.06	.44
503	64,029	.18	2.36	.60
504	79,074	.13	.98	.61
505	91,664	.11	.44	.53
601	69,086	.11	1.24	.48
602	84,444	.09	.80	.35
603	82,120	.18	.67	.42
604	70,316	.08	.60	.31
605	78,670	.1	.74	.31
606	98,219	.11	.59	.30
701	81,390	.15	.66	.15
702	60,493	.21	.18	.10

This table reports the weighted-average family income, vacancy rate, renter-to-owner occupancy ratio, and minority share by MLS Area. The variables are constructed using census tract statistics from the 2014-2018 ACS, 5-year estimates.

Table A.2: Event Study of MLS Area Labeling Effects

	(1) ln(Price) Sales	(2) ln(Rent) Leases
Minority Share × 2020Q1 or before (l=-6$^+$)	-0.248***	0.023
	(-17.003)	(1.120)
Minority Share × 2020Q2 (l=-5)	0.026	0.026
	(1.103)	(1.229)
Minority Share × 2020Q3 (l=-4)	0.010	0.023
	(0.479)	(0.960)
Minority Share × 2020Q4 (l=-3)	0.034	0.018
	(1.477)	(0.876)
Minority Share × 2021Q1 (l=-2)	0.016	-0.013
	(0.700)	(-0.609)
Minority Share × 2021Q3 (l=0)	0.041**	0.024
	(1.996)	(1.021)
Minority Share × 2021Q4 (l=1)	0.101***	0.088***
	(4.478)	(3.713)
Minority Share × 2022Q1 (l=2)	0.115***	0.101***
	(5.261)	(4.384)
Minority Share × 2022Q2 (l=3)	0.129***	0.096***
	(5.949)	(4.735)
Minority Share × 2022Q3 (l=4)	0.187***	0.089***
	(7.021)	(3.879)
Minority Share × 2022Q4 (l=5)	0.220***	0.092***
	(4.480)	(3.693)
Observations	170,580	20,397
Adjusted R-squared	0.945	0.967
Singletons	186,344	37,258
Tract Controls	✓	✓
Parcel FE	✓	✓
Year-Quarter FE	✓	✓

This table reports OLS estimates of the Area Minority Share effect by event date from MLS Area censorship on the natural log of price for sold properties in column (1) and leased properties in column (2). The samples consist of transactions from 2013 to 2022 for sales and 2020 to 2022 for leases in Clark County, NV. Each interaction represents properties listed at time l quarters from the MLS Area censorship quarter, which occurred on 2021Q3 (l=0). The reference group (where l=-1) are properties listed in 2021Q2. *Area Minority Share* is the proportion of individuals within the same MLS Area that are not non-Hispanic White as of the 2018 ACS, 5 year-estimates. Tract characteristics include ln(Tract Median Family Income), ln(Tract Median Gross Rent), Tract Capitalization Rate, Tract Hispanic Share, Tract Black Share, Tract Vacancy Rate, and Tract Renters-to-Owners Ratio. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.3: Minority Share and Missing MLS Area Field

	(1) 1[Missing] Sales 2021Q3	(2) 1[Missing] Sales 2021Q4	(3) 1[Missing] Leases 2021Q3	(4) 1[Missing] Leases 2021Q4
Minority Share	0.185	-0.055	0.079	-0.008
	(1.281)	(-1.217)	(0.361)	(-0.119)
ln(Tract Median Family Income)	-0.036	-0.005	-0.059	-0.025
	(-1.068)	(-0.584)	(-1.178)	(-1.451)
ln(Tract Median Gross Rent)	0.006	-0.002	-0.019	0.019
	(0.133)	(-0.165)	(-0.298)	(0.730)
Tract Capitalization Rate	-0.347	-0.047	0.164	-0.216
	(-1.211)	(-0.727)	(0.712)	(-1.229)
Tract Hispanic Share	0.010	-0.003	-0.020	-0.013
	(0.148)	(-0.161)	(-0.186)	(-0.409)
Tract Black Share	-0.170	0.011	-0.268	-0.068
	(-1.511)	(0.438)	(-1.583)	(-1.398)
Tract Vacancy Rate	-0.118	-0.003	0.000	-0.029
	(-1.393)	(-0.168)	(0.001)	(-0.836)
Tract Renters-to-Owners Ratio	0.004	0.001**	-0.002	-0.000
	(1.059)	(2.106)	(-0.539)	(-0.199)
Observations	11,075	8,195	4,599	4,281
Adjusted R-squared	0.002	0.001	0.001	0.001
Singletons	0	1	0	0
ZIP code FE	✓	✓	✓	✓

This table reports OLS estimates of the Minority Share in an Area on the likelihood of Censorship. The sample is restricted to observations in 2021Q3. *Minority Share* is the proportion of individuals within the same MLS Area that are not non-Hispanic White as of the 2018 ACS, 5 year-estimates. t-Statistics using robust standard errors clustered by parcel id are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.4: Probit Regression on Treatment

	(1) 1[Treatment]
ln(Tract Median Family Income)	-0.397***
	(0.093)
ln(Tract Median Gross Rent)	0.498***
	(0.093)
Tract Hispanic Share	0.616***
	(0.112)
Tract Black Share	-0.134
	(0.160)
Tract API Share	1.084***
	(0.184)
Tract Vacancy Rate	1.235***
	(0.193)
Tract Renters-to-Owners Ratio	0.023
	(0.020)
Conv Mortgage Rejection Rate	-0.428
	(0.361)
FHA Mortgage Rejection Rate	-0.272*
	(0.159)
Average Appraised Value Growth	4.682***
	(0.411)
Observations	41,489

This table reports coefficient estimates of a Probit model of Treatment on 2018 ACS 5-year estimates. The sample consists of nationwide census tracts (excluding AL, AZ, GA, and LA). Treatment takes a value of 1 if the census tract is in Clark County, NV; otherwise it is 0.

Table A.5: Hedonic Rent Model

	(1) Rent/SQFT Leases
ln(Living Area Square Feet)	-4.786***
	(-14.970)
ln(Lot Size Square Feet)	0.095***
	(3.418)
Age of Building	-0.086***
	(-3.481)
Beds Total	-0.192**
	(-2.128)
Baths Total	-0.024
	(-0.348)
Fireplaces	0.323***
	(3.715)
Garage	0.562***
	(8.119)
Private Pool	1.757***
	(20.721)
Private Spa	0.742***
	(11.644)
Property Type: Condominium	0.848***
	(3.049)
Property Type: 2-4 Unit	-0.409**
	(-2.523)
Observations	259,282
Adjusted R-squared	0.726
Singletons	200
ZIP-Year-Quarter FE	✓

This table reports OLS estimates of property characteristics on the monthly rental rate per square foot. The sample consists of lease transactions from 2013 to 2022 in Clark County, NV. t-Statistics using robust standard errors clustered by zip code are reported in parentheses. The stars ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.6: Summary Statistics of HMDA data

	Observations	Mean	Std. dev.	min	max
Panel A - Minority Share					
non-Hispanic White	3,413	0.14	0.17	0	0.66
non-Hispanic Black	3,413	0.07	0.09	0	0.39
non-Hispanic Asians	3,413	0.06	0.09	0	0.41
Hispanic	3,413	0.51	0.20	0.16	0.91
Panel B - Log Income					
non-Hispanic White	872	4.24	0.30	3	4.98
non-Hispanic Black	433	4.08	0.29	3	5.12
non-Hispanic Asians	360	4.15	0.44	0	5.84
Hispanic	1,748	3.97	0.21	3.27	4.48
Panel C - Age					
non-Hispanic White	872	44.07	4.77	30	62
non-Hispanic Black	433	44.98	6.39	25	70
non-Hispanic Asians	360	44.17	4.83	30	63.33
Hispanic	1,748	39.04	2.81	33.70	52.50

This table presents summary statistics for the treated high-minority tracts in 2020 in the HMDA dataset, including the number of observations, average value, standard deviation, and minimum and maximum values. The treated census tracts are in Clark County, NV. Panel A presents the minority share for different racial groups, whereas Panel B presents summary statistics of log income, and panel C presents summary statistics of age by racial groups. Source: Home Mortgage Disclosure Act (HMDA) database.

Table A.7: Summary Statistics of CCP data at the tract-level

Panel A - 2020	Observations	Mean	Std. dev.	min	max
Move-In	201	0.163	0.395	0.073	0.297
Move-Out	201	0.194	0.048	0.063	0.348
Equifax Risk Score	201	663.4	20.5	614.9	720.0
Panel B - 2022	**Observations**	**Mean**	**Std. dev.**	**min**	**max**
Move-In	201	0.172	0.047	0.045	0.311
Move-Out	201	0.110	0.034	0.015	0.194
Equifax Risk Score	201	673.1	21.1	630.6	728.7

This table reports summary statistics for the treated high-minority tracts (minority share above half) in 2020 (Panel A) and in 2022 (Panel B). The Table includes the number of observations, average value, standard deviation, and minimum and maximum values. The treated census tracts are in Clark County, NV. We limit the age of the consumers in the data to be between 18 to 95. If a customer has a registered change in their FIPS code in the last (next) 18, 12, and 6 months, they are marked as an in-migrants (out-migrants) "mover". Likewise, we set the dependent variable as the average Equifax Risk Score in the tract. Equifax consumer credit reports and Equifax data assets do not contain information about consumer's race or gender. Source: FRBNY Consumer Credit Panel (CCP)/Equifax dataset.

Table A.8: Summary Statistics of consumers that moved in to the treated high-minority tracts at the consumer-level

Panel A - 2020	Observations	Mean	Std. dev.	min	max
Out of State	31,153	0.108	0.069	0	0.357
In State	31,153	0.897	0.067	0.642	1
Panel B - 2022	**Observations**	**Mean**	**Std. dev.**	**min**	**max**
Out of State	30,881	0.121	0.072	0	0.375
In State	30,881	0.881	0.071	0.625	1

This table reports summary statistics for the consumers that moved in to the treated high-minority tracts (minority share above half) in 2020 (Panel A) and in 2022 (Panel B). The Table includes the number of observations, average value, standard deviation, and minimum and maximum values. The treated census tracts are in Clark County, NV. We limit the age of the consumers in the data to be between 18 to 95. If a customer has a registered change in their FIPS code in the last (next) 18, 12, and 6 months, they are marked as an in-migrants (out-migrants) "mover". Equifax consumer credit reports and Equifax data assets do not contain information about consumer's race or gender. Source: FRBNY Consumer Credit Panel (CCP)/Equifax dataset.

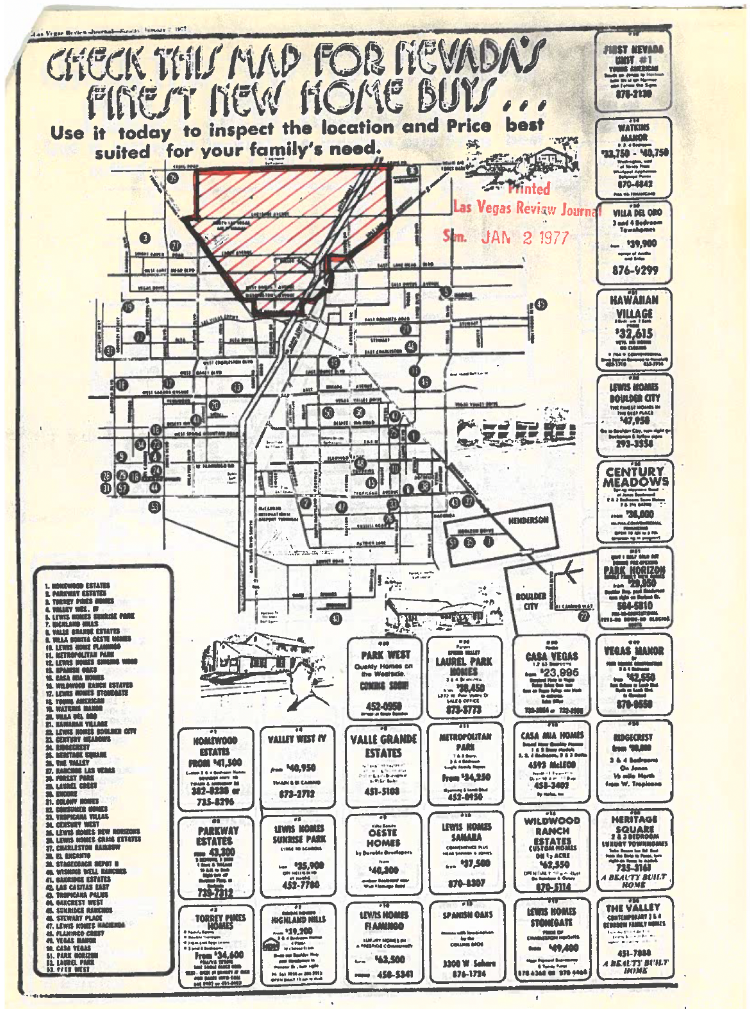
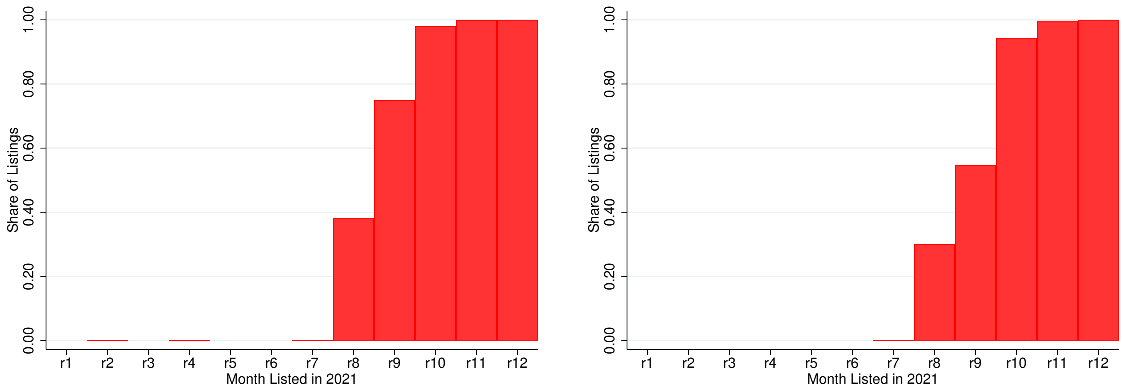


Figure A.1. Las Vegas Redlining Map

This figure exhibits a map of Las Vegas by the Las Vegas Review-Journal anonymously marked in red pen showing where redlining possibly occurred. The original record is available at Special Collections and Archives, University Libraries, University of Nevada, Las Vegas, MS-00246, Box 04 (1959-1988).



(a) Sales

(b) Leases

Figure A.2. Share Missing MLS Label in 2021

This figure reports the share of sales observations (a) and rent observations (b) by the month listed on the LVR-MLS platform. The sample is restricted to properties listed in 2021.

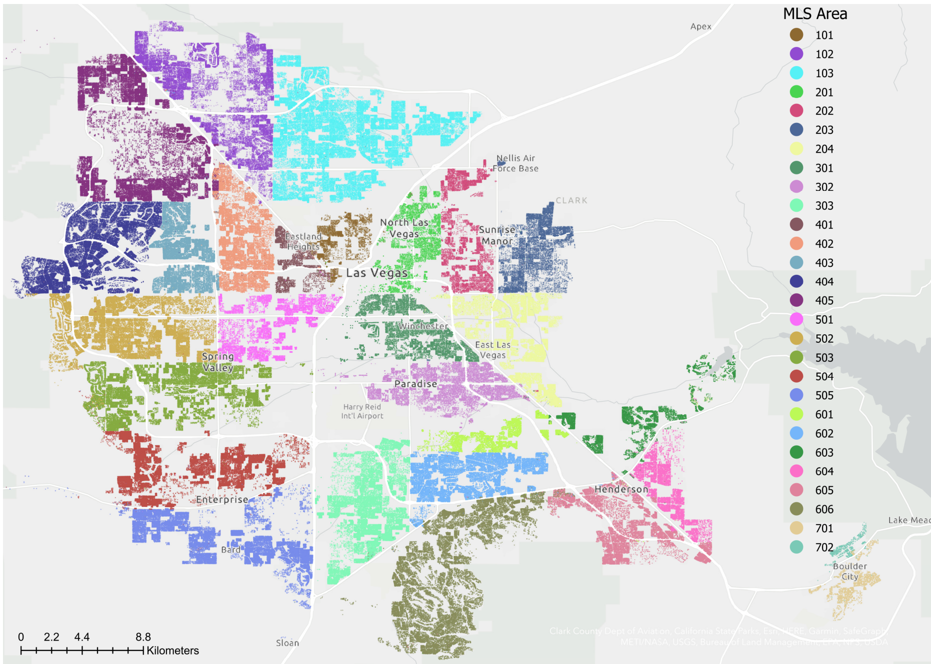


Figure A.3. Realtor MLS Area Data

This figure maps observations from the Sales and Lease LAR-MLS data. Observations are color-coded by reported MLS Area classification.

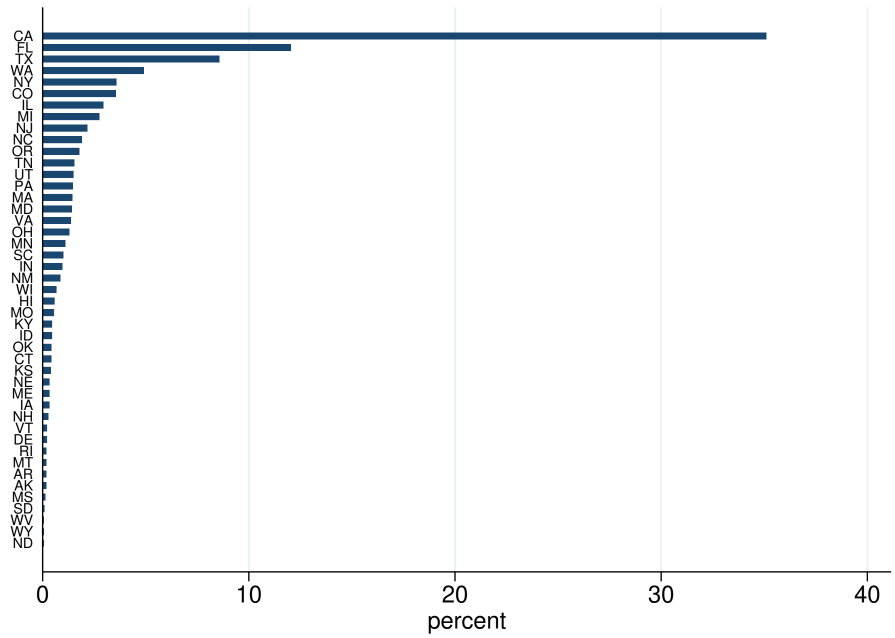
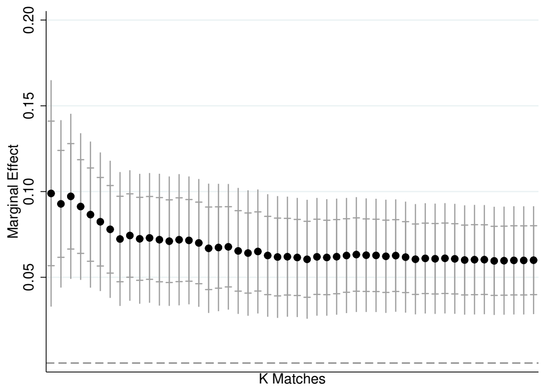
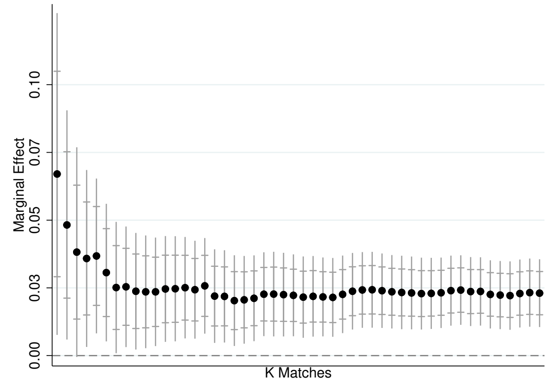


Figure A.4. Matched Control Tract by State

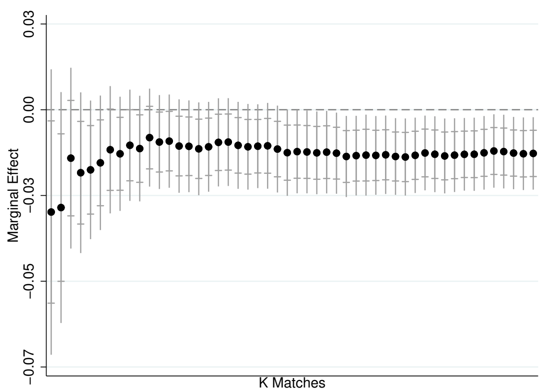
This figure shows the proportion of census tracts by state in the matched control sample.



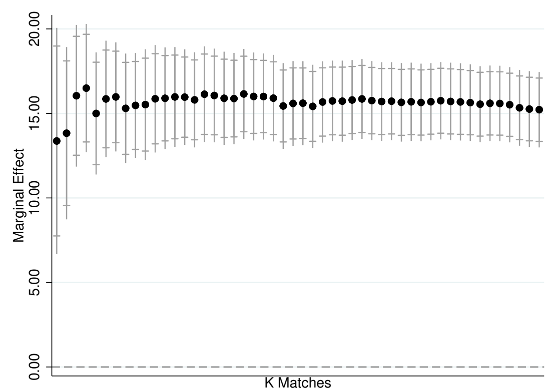
(a) Appraisal Mean Value



(b) Appraisal Mean Distance



(c) Appraisal Share Common Tract



(d) Appraisal Purchase Count

Figure A.5. Sensitivity of Appraisal Statistics to K-Nearest Neighbor Matches

This figure reports the average response to censorship estimates for 1 to 50 k-nearest neighbor matching alternative models.

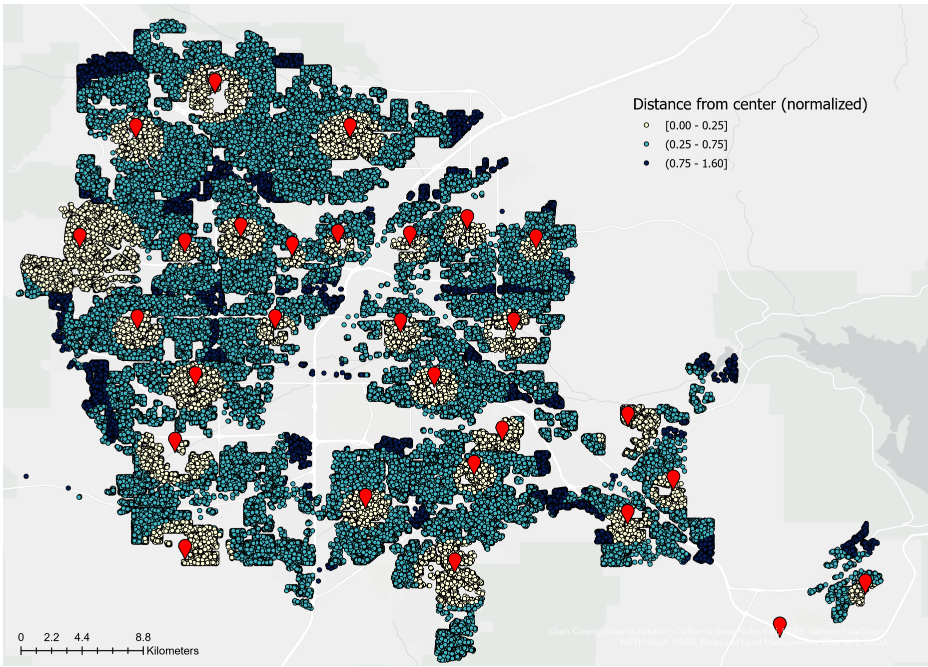


Figure A.6. Distance from MLS Area Centroids - Sales Data

This figure maps observations from the Sales LAR-MLS data. Observations are color-coded by the relative distance from Area centroids. The red pin represent MLS Area centriods, which are based off population weighted 2010 census tract centroids.

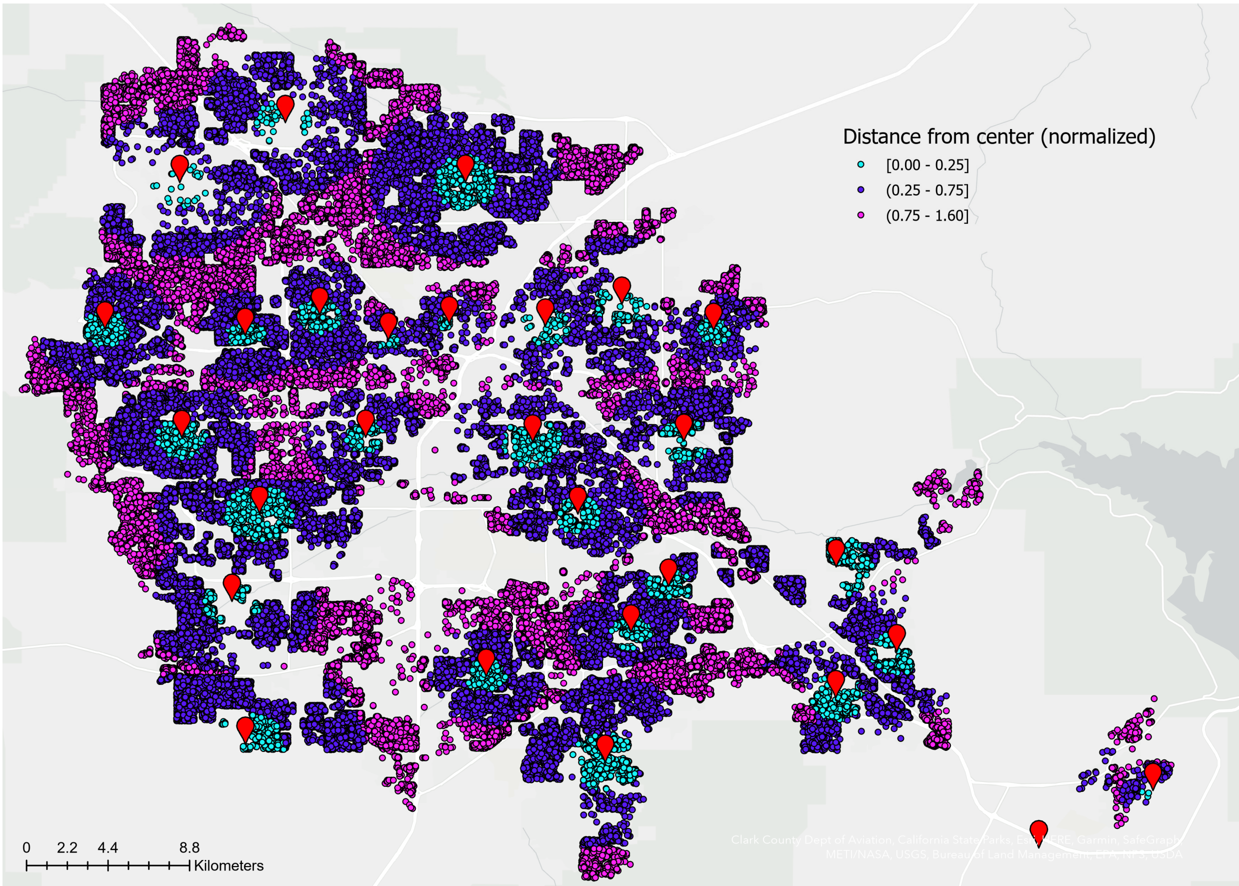


Figure A.7. Distance from MLS Area Centroids - Lease Data

This figure maps observations from the Lease LAR-MLS data. Observations are color-coded by the relative distance from Area centroids. The red pin represent MLS Area centriods, which are based off population weighted 2010 census tract centroids.