# Density Zoning Interacts With Racial Diversity: New Evidence From National Data \*

Tianfang Cui New York University tc4089@nyu.edu<sup>†</sup> Vicki Been New York University vicki.been@nyu.edu

November 14, 2024

### Abstract

We study the role density zoning plays in neighborhood racial change with a new spatial dataset of regulatory borders. Combining geocoded property records with estimates of minimum lot size restrictions within U.S. cities, we identify the borders of areas where sharp shifts occur in the maximum allowable residential density. Merging that border data with the demographics of Census blocks on each side of the border, we estimate how minimum lot sizes contribute to differences in the racial diversity of neighborhoods. We find that the effects minimum lot sizes have on racial diversity vary significantly, depending on the urban context. Effects are strongest in areas of higher density suburban development. There, lot size restrictions that decrease density by 2 units per acre relative to areas on the other side of the regulatory boundary cause sizable declines in diversity. Effects fade when one or more sides of the boundary has minimum lot requirements above a quarter acre in effect. Our results show the circumstances in which lot size regulations stymied racial integration and persistently hindered fair housing goals in the following decades.

Latest version available here

\*We thank participants at the NYU Furman Center and the Wharton School for comments. Cui gratefully acknowledges support from the Zell-Lurie Real Estate Center Research Sponsor Program at Wharton. Been gratefully acknowledges the support of the Filomen D'Agostino and Max E. Greenberg Research Account.

Although this research was conducted by researchers affiliated with the NYU Furman Center, which is affiliated with NYU's School of Law and Wagner Graduate School of Public Service, it does not purport to present the institutional views (if any) of NYU or any of its schools.

<sup>&</sup>lt;sup>†</sup>Corresponding author.

# 1 Introduction

Residential integration by race and by economic status limits the costs of segregation (Ananat, 2011) and compounds the positive effects of moving to economically diverse neighborhoods (Chyn, 2018). Of all the frictions that slow residential integration and that policy interventions can correct (Bergman et al., 2024), local governments' land use regulations pose persistent barriers. It is well established that zoning regulations and other government land use policies segregated neighborhoods by race and class, both in intent and in practice (Rothstein (2017); Trounstine (2020)). Less well understood is which particular regulations continue to stymie integration; whether reforming those regulations will result in greater racial or economic diversity; and which reforms will be most cost effective.

Our paper quantifies the barriers to integration posed by one type of regulation: density zoning, which restricts the sizes of housing that the market can supply. Most American local governments require each new housing unit to use up a minimum amount of land, restricting density through minimum lot sizes. We provide new measures of how lot size requirements, from small to large, are imposed across the largest U.S. cities. We study whether (and if so, which) minimum lot sizes caused disparities in racial makeup at a local scale: between blocks where a particular lot size regulation applied and adjacent areas where the same limit does not apply. These disparities let us evaluate how lot size restrictions of various sizes affected racial integration of American neighborhoods over time.

Local governments apply density zoning unevenly across space. Collecting the maps that record those regulatory decisions, lot size restrictions among them, is a costly process with no comprehensive standard dataset yet in use. An ideal research design to estimate a causal effect of minimum lot sizes requires not just maps, but more granular information. We would want to use variation only close to boundaries across which lot size regulations change. We would also know that the boundaries were not defined to keep desirable land and existing development all on one side, in which case differences in racial diversity in what was built later were based upon neighborhood characteristics other than required lot sizes.

Our first contribution is introducing an automated method for detecting borders between areas where properties were developed with different lot sizes. With geocoded data at the lot level, we can detect sharp transitions between lot sizes that are all above a regulatory minimum to lot sizes lower than that value. We build a sample of properties where the localized lot size minimum matches independent estimates of lot size regulations that were binding on developers. For each regulatory minimum, we detect approximately straight border segments across which maximum density increases. The variation we capture over certain kinds of border segments, compared to entire zoning district borders, better reflect the ideal research design.

We use conventional and scalable machine learning algorithms in the automated procedure to process administrative assessment records. We identify the sizes of lots within each jurisdiction and reveal borders between areas within jurisdictions in which allowable density shifts. 120 of the largest U.S. metropolitan areas.

We then use our detected minimum lot size border segments in a border discontinuity design, comparing differences in demographic composition of Census blocks on both sides of the border at various points in time. We only examine demographic outcomes in narrow bands on either side of the regulatory border, using data-driven bandwidths. For each segment, we use only those blocks within a single jurisdiction. These sample restrictions prevent our results from being driven by differences in local public goods, by neighborhood amenities unrelated with zoning differences and by functional form specifications.

When all segments are pooled together, the average effect of minimum lot sizes on racial disparities is precise and small. Whether in 1980 or in 2020, the average difference in block-level racial minority shares across lot size borders is than one percentage point. While the null hypothesis can be rejected with above 99% confidence, the resulting estimand is unlikely to be policy relevant. First, a minimum lot size can mandate a wide range of densities. A city is unlikely to adopt a combination of regulations that correspond to the average effect. Second, the same regulation applied in two cities may cause different marginal shifts in surrounding density. Evaluating the role of minimum lot sizes, as it was applied between cities or within neighborhoods, should go beyond extrapolating average effects.

To derive neighborhood-level, policy relevant effects of minimum lot sizes on racial diversity, we accordingly define and estimate *urban context-specific effects*. Instead of averaging over all existing regulations, we allow variation based on both the regulatory requirement and on the increase in lot sizes it mandates relative to the segment's surrounding residential development. Unlike prior studies that use data from at most one metropolitan area, we use cross-sectional variation within cities where over 240 million Americans live. We have enough statistical power to drill down on changes in racial diversity due to variations between adjacent areas developed at different lot sizes.

At this level of heterogeneity, we show three main results. First, our estimates reveal context-specific racial disparities of as much as 3 to 7 percentage points. The context in question are denser suburbs, built up at around 10-12 dwelling units per acre (DUPAC). The minimum lot sizes generating the largest disparities matter on the margin, in that they reduce allowable density by two or more DUPAC. Second, the estimates show that disparities in racial

diversity as of 2020 persist to the same extent as they did as early as 1980. For restrictive lot sizes in denser suburbs, these disparities have even grown over time.

Finally, we show that sizable racial disparities appear only when both the surrounding development and the areas "treated" with lot size regulations have what are now considered small lot sizes. The effects lot sizes have on racial diversity decrease as the minimum lot size generates smaller marginal increases in lot sizes relative to adjacent areas. We find that when the marginal increase due to regulation is less than 4000 square feet, point estimates of lot size effects on racial shares is close to zero and statistically insignificant. More surprisingly, when the regulated zones require lot sizes of more than a quarter acre, we do not see large racial disparities even when the surrounding urban context is dense. One possibility is that, once jurisdictions have a large lot size zone somewhere within its borders, even the dense neighborhoods in the jurisdiction are valued at a premium relative to other jurisdictions.

We run two additional analyses to verify that our effects are not driven by explanations other than the adoption of minimum lot sizes. We first check for the presence of discontinuities in housing market conditions that can confound racial disparities. We do not find statistically significant discontinuities in 1980, the start of our sample, in the share of home-ownership or in the age distribution of residents across lot size regulatory borders. Second, we run separate analyses between postwar developments built up a about the same time as lot size minimums were adopted, and post-1980 developments, built up following widespread adoption by the 1970s. Our findings do not suggest results are driven by other characteristics of postwar neighborhoods. In fact, our point estimates for racial disparities are larger along lot size borders for newer developments.

Our paper first provides a new source of data that is the best current approximation of when particular lot size minimum restrictions were imposed in jurisdictions across the country. This data contribution is in line with with recent advances in nationally representative zoning data (Bronin et al. (2023), Song (2024), Macek (2024)), using the latest zoning district information. At the cost of not outputting entire district borders, our approach uses spatial and historical information to classify how endogenous different border segments were. We aim to filter out sections of zoning borders determined by market demand, like borders drawn to recognize what was built or desirable undeveloped land.

We provide evidence that a specific regulatory strategy — lot size requirements large enough to impose a *de facto* minimum entry fee to live in the neighborhood — continues to have effects on racial composition in neighborhoods subject in part to them. As state and local governments across the United States grapple with how to reform land use regulations to address the housing crisis, our evidence helps bolster the case that allowing denser housing in jurisdictions that have practiced exclusionary zoning could both increase housing supply and increase racial diversity. Moreover, increasing density may be far more effective outside of neighborhoods with very substantial lot size requirements.

In addition, in its most recent decision regarding the Fair Housing Act, the Supreme Court insisted that plaintiffs seeking to prove that a policy has a disparate impact on different racial groups must point to a specific policy, and show "robust causality" between that policy and the disparate impact. Our findings should satisfy that burder of proof for challenges to lot size requirements, emphasizing the effect of relatively small minimum lot size requirements subject to fewer legal challenges in the past (Gardner, 2024)

Our results also relate broadly to the analysis of residential segregation and white flight. Recent work has modelled present-day *homophily preferences* to live with residents of the same race, predicting continued instability in neighborhood racial composition (Davis, Gregory and Hartley (2023), Caetano and Maheshri (2023)). Compared to the rate of white flight per new Black resident in postwar central cities, the same rate is lower in suburban neighborhoods today (Bartik and Mast, 2023). By finding persistent racial disparities around lot sizes, we offer new evidence that the presence of density zoning can mediate how, and if, neighborhoods undergo rapid racial change.<sup>1</sup>

The rest of the paper proceeds as follows. Section 2 describes the historical development of local governments' adoption of minimum lot sizes up to 1970, as well the growing diversity of U.S. suburban neighborhoods since then. Section 3 illustrates the automated method for detecting lot size borders and summary statistics on the output dataset. Section 4 defines urban context-specific effects for lot size regulations and the modern methods we use to estimate effects while minimizing sources of bias. Section 5 presents our main results, while Section 6 discusses their significance for policy and compared to estimates in the literature. Section 7 concludes.

<sup>&</sup>lt;sup>1</sup> A body of recent research studies how historical legal restrictions can cause long-run changes in neighborhood demographics (Aaronson, Hartley and Mazumder (2021), Shertzer, Twinam and Walsh (2022), Sood and Ehrman-Solberg (2024)). Boundaries defined in the past can also shape urban form and residential sorting patterns over time (Gyourko and McCulloch (2023), Gallagher, Shertzer and Twinam (2024), Maheshri and Whaley (2024)). Our estimates show persistent impacts of one of the most common types of land use regulation: density zoning that created residential patterns at lower densities than the market supplied in adjacent areas not subject to the density restriction.

# 2 History and Context

**Overview of U.S. Minimum Lot Size Adoption.** Recent legal research situates the start of density zoning through minimum lot sizes from the 1920s to the 1940s (Gardner, 2023). After New York City adopted the first citywide zoning ordinance in 1916, the U.S. federal government promoted zoning regulations by drafting the 1922 "Standard State Zoning Enabling Act." The model law enabled local governments to divide their jurisdiction into districts and within each district regulate matters of development: the size of buildings, the share of a lot that a building may occupy, the size of yards, courts and other open spaces, and general density (Advisory Committee on Zoning, 1926). Most states adopted the model act or some close variant, after which lot size restrictions would appear as a form of density regulation.

While we lack good text records on when and what kinds of density restrictions were adopted in jurisdictions across the United States over the ensuing decades, Cui (2024) uses an algorithm to estimate adoption dates of the first minimum lot sizes. The algorithm identifies lot sizes of new developments occuring significantly more frequently than marginally larger or smaller sizes. By incorporating information on such "bunching on lot sizes" and a training set of known zoning ordinances, the algorithm can scale up measurement of of when the first minimum lot size regulations were adopted in suburban jurisdictions with sizable single-family housing<sup>2</sup>

Panel (a) of Figure 1 plots results from Cui (2024) on first adoption of any lot size, along with adoption of lot sizes above 7,500 square feet — about a sixth of an acre. That paper finds the widespread use of minimum lot sizes is mainly a postwar phenomenon. Of the towns and cities that have at least 5,000 residents by 2010, four-fiths of those sizable jurisdictions adopted by 1970 some kind of restrictive minimum lot size. Adoption of multiple minimum lot sizes over different districts was common, and two-thirds of jurisdictions had a lot size requirement above 7,500 square feet. The rate of adoption after 1970 slowed considerably.

Minimum lot size restrictions, with perhaps the exception of those below 5,000 square feet, does not obviously improve building safety (Gardner, 2023). The regulations offer a facially race-neutral approach, defensible in courts, to exclude development of lower cost single family homes, rowhomes and multifamily buildings. Cui (2024) found, however, that the Great Migration of Black Americans to urban areas from 1940–1970 caused responses in when and what minimum lot sizes were adopted in jurisdictions surrounding urban areas. Greater arrival rates of Black migrants into cities caused zoning that further restricted the contemporary supply

<sup>&</sup>lt;sup>2</sup>Conversely, the algorithm is less effective at detecting density zoning in built-up cities. It is not meant to identify the earliest lot size requirements, put in place for reasons of fire safety.

of housing density, using a bunching measure of regulatory restrictiveness. The effects are small and in the opposite direction for urban areas where the Southern migrants were white.

The practical implication of those regulations has been to exclude lower income households, in certain neighborhoods within jurisdictions. The enforcement of Fair Housing legislation from the 1970s onwards have not targeted reversal of local governments' past zoning decisions. Given the correlation between race and income, we expect that lot size restrictions also exclude disproportionate numbers of Black households.

**Growing Racial Diversity in U.S. Suburbs.** The spread of minimum lot size regulations accelerated with postwar suburbanization, and the initial movers to the suburbs were white Americans experiencing income growth (Margo). Highway expansion beyond the urban fringe caused population growth beyond central cities (Baum-Snow, 2007), while urban neighborhoods built before the war saw white flight and rapid racial transitions (Card, Mas and Rothstein (2008), Boustan (2010)) However, indices of residential segregation has declined at a steady pace since 1970 (Glaeser and Vigdor (2012), Bartik and Mast (2023)). Just as the first suburbanites could afford lot size restricted homes in previous decades, income growth among all people of color could have expanded the choice set of neighborhoods affordable to them.

The trends in suburbanization and in income growth can be seen in the data. story is Panel (b) of Figure 1 plots the likelihood of different racial groups to live outside of a metro's central city. We tabulate residential statistics from the Census Bureau for all of the nearly 390 Metropolitan Statistical Areas (MSA), then delineate the central city of each MSA based on 1960 city borders<sup>3</sup> We follow Bartik and Mast (2023) and calculate the suburban share as the share of a group not living in historical central city borders.

The trends in Panel (b) show that racial minorities, defined as Americans except Non-Hispanic White Americans, have been steadily moving out of neighborhoods in central cities. The suburbanization rate went from 38% in 1980 to 72% in 2020. A slower, but similar trend holds for Black Americans, from 33% in 1970 to 66% by 2020.

Panel (c) plots growth in real mean household incomes, as calculated from Current Population Survey (CPS) data. We plot both mean incomes for Black Americans and Non-Hispanic White Americans, as well as a series summing over all racial minority groups. While the gap in mean incomes between these three series have not converged, the lack of further widening shows Americans who are part of a racial minority have seen a level growth of at least 170%

<sup>&</sup>lt;sup>3</sup> The 1960 borders are approximated from tract-level data, and their construction are further explained in Cui (2024). We use historical borders due to strategic annexation of suburbs by certain central cities in the postwar decades. Central cities based on 1960 borders, however, should include residential development patterns mostly prior to postwar suburbanization.

in their household incomes since 1980.

While it is unsurprising that real income growth is correlated with suburbanization, income growth should also lessen the constraint minimum lot sizes impose on access to suburban neighborhoods. A neighborhood where a minimum lot sizes is larger than the density of surrounding development implements additional housing consumption needed to access a neighborhood (Kulka). If the required increase in consumption gets smaller relative to the housing services new residents can purchase, we would expect minimum lot sizes adopted during postwar decades would lose their exclusionary power and would not persistently cause racial disparities. Conversely, the largest disparities should be found where dense development gives way to larger lot size requirements.

# **3** Measuring Lot Size Borders

In this section, we describe the detection procedure we use to create our dataset of minimum lot size borders. We start with the dataset described in Cui (2024), which exploits information on how development bunches at certain lot sizes for both older and newer vintages of a city's housing stock. The algorithms introduced in that paper is scaled nationally, producing for each jurisdiction a set of lot sizes where the bunching behavior is consistent with what a binding minimum lot size would generate.

Our objective is to use that dataset to detect, within each jurisdiction, segments of borders where lots around those bunching sizes give way to denser development. The intent is not to recover the full collection of boundaries separating different residential zones, as communicated through a jurisdiction's zoning map. Rather, we isolate segments that are sufficiently straight over a minimum distance, a criterion also used in Turner, Haughwout and van der Klaauw (2014) and Kulka, Sood and Chiumenti (2023).

By including only sufficiently straight segments of zoning borders, we can more justifiably assume that the characteristics of land on both sides of the border are not systematically different. Where a restrictive minimum lot size is applied based on which side of an "arbitrary" border segment the property falls, we expect no other spatially stratified confounders that would predict supply of different housing characteristics on just one side.

Other methods in the literature for detecting changes in minimum lot sizes (Song (2024), Macek (2024)) take lots labelled based on zoning codes, approximate residential zoning boundaries using clustering or imputation methods and retrieve the binding minimum lot size in each zone. Our detection procedure differs by taking a set of lot sizes to investigate and outputs spatial features (i.e. borders). To each segment, we can also check if homes around the segment were built before and after the estimated first adoption of minimum lot sizes for that jurisdiction. We explain briefly why the bunching information in Cui (2024) should map to actual regulations. However, the procedure can also accept other datasets constructed through other means<sup>4</sup>

### 3.1 Overview of border detection

To detect the desired border segments, our procedure proceeds in parallel across a tiling of the interior of each zoning jurisdiction. Each border segment is a line long enough to divide the tile, such that we can label one of two sections as where a minimum lot size restricts development. We accept the border if, under these constraints, there is a low enough misclassification rate of small lots into the restrictive lot size section.

To illustrate this process, we apply the procedure on a sample jurisdiction: Lower Merion Township, a suburb of Philadelphia, PA. The remainder of this Section repeatedly references Figure 2, a schematic showing how the procedure operates within Lower Merion. The schematic assumes a parametrization behind the procedure which is further detailed in Section 3.2.

**Choice of zoning jurisdictions and tiling over jurisdictions.** Our definition of zoning jurisdiction accounts for state-varying standards in what levels of local government decide zoning. In nearly all states, incorporated places (e.g. cities or villages) have the zoning power; in most states, counties have the zoning power over the remaining unincorporated land. We also account for Northeastern and Midwestern states delegating the zoning power to minor civil divisions, like towns and townships.<sup>5</sup>

Using U.S. Census Bureau shapefiles, we define the boundary and interior of each zoning jurisdiction across Metropolitan Statistical Areas (MSAs). Then, over each MSA geography, we apply a uniform hexagonal tiling of radius R; the second inset of Figure 2, Panel (a) shows the subsection that covers Lower Merion. Any tile that contains parts of two or more jurisdictions is defined as a *boundary tile*.<sup>6</sup> Only the complement, the *interior tiles*, are used for the rest of our procedure.

<sup>&</sup>lt;sup>4</sup> For example, Bartik, Gupta and Milo (2024) processes numerous present-day zoning ordinances to retrieve minimum lot sizes for jurisdictions. If we assume all those present-day regulations were adopted in the past, we can use those authors' data as the regulatory data inputted into the procedure.

<sup>&</sup>lt;sup>5</sup> The appendix of Cui (2024) offers further details on zoning jurisdiction classification by state.

<sup>&</sup>lt;sup>6</sup> When separating out boundary versus interior tiles, we treat unincorporated land annexed to incorporated places after 1980 as a special case. If development within those annexed boundaries were primarily built before 1975, we treat the tiles around present-day borders as interior tiles of the unincorporated county jurisdiction. Otherwise, we remove those present-day border tiles from the ensuing analysis.

**Merging lot-level records and regulation data.** We use CoreLogic tax assessor records to retrieve lot-level characteristics for individual single-family and duplex homes. The detection procedure exploits two key variables: the property's lot size and its location. Because CoreLogic geocoded its assessor records, properties can be assigned to precise coordinates. We confirmed that availability of these two variables is almost universal in all the MSAs we examine.

We also merge, to each jurisdiction, lot size regulations measured through a bunching algorithm applied in Cui (2024). The key idea behind that algorithm is that by comparing lot size distributions of older to newer homes in each jurisdiction, the emergence and persistence of bunching around certain lot sizes in those distributions are informative about the minimum lot size regulations that restricted denser development. Once applied at scale, the algorithm in Cui (2024) outputs *bunching bins* that maps to lot size regulations, as well as a measure of when the jurisdiction first adopted minimum lot sizes of any kind.

Filtering to tiles with possible lot size borders. Given a lot size regulation detected through bunching  $\underline{\ell}$ , part of the jurisdiction will be under residential zones where that regulation applies. The data should satisfy two criteria if a relevant border segment of these zones passes through an interior tile. First, there should be a positive number of lots smaller than the minimum required in the zones. Second, there should be a significant number of lots of size between the regulatory minimum,  $\ell$ , and an upper bound  $M \cdot \ell$ .

We filter again to keep only the interior tiles that has at least N lots with sizes between  $[\underline{\ell}, M \cdot \underline{\ell}]$ , followed by at least 0.4N lots with sizes less than  $\underline{\ell}$ . The rightmost inset of Figure 2, Panel (a) shows this process applied to the 30,000 square feet minimum lot size in Lower Merion.

The coloured dots represent lots between  $[\underline{\ell}, M \cdot \underline{\ell}]$  square feet. Under the parameters we use, the filter is not overly restrictive and we keep tiles covering a majority of lots near the regulatory minimum. The tiles we exclude either contain too few small lots, so it is likely they do not have any zoning border running through them; or have too few lots near the minimum, in which case we believe the development would have been built regardless of the density zoning in effect.

Within-tile detection of border. By construction, within each remaining tile there are lots both smaller and larger in size than the regulatory minimum  $\underline{\ell}$ . In the leftmost inset of Figure 2 Panel (b), we zoom into a single tile and classify all lots into two categories based on size relative to  $\underline{\ell}$ . Following this labelling, detecting a border segment turns into finding a linear classifier that minimizes misclassification error.

We apply the support vector machine (SVM) classifier which takes two features, the lots' longitude and latitude, as input vectors. The classifier then trades off allowing fewer misclassified samples versus minimizing separation from misclassified outliers. Appendix C explains the exact objective function in more detail.

In the example in Figure 2, visual inspection shows a roughly linear boundary divides the two lot classes. Additionally, there are small outlier lots below 30,000 square deep in one class, and vice versa. The SVM classifier follows this intuitive boundary well, and outputs a misclassification error  $m_{err} = 15\%$ .

This procedure, scaled up to all of Lower Merion, results in spatial features like the rightmost inset of Panel (b). We both obtain the borders of zones where lot size minimums apply, as well as the border regions of those zones highlighted in purple. Our approach can be contrasted with naive classification method — keeping all the tiles with a median lot size above the regulatory threshold, and looking at the borders of that region. In the Lower Merion example, the border tiles of that method are mostly surrounded by the interior tiles where we successfully detect bisecting zoning borders.

To finalize our preferred sample of sufficiently straight boundary segments, we keep only segments whose misclassification error is below a threshold  $\overline{m_{err}}$ . Above this threshold, we are concerned the actual borders of residential zones is not straight, or no actual borders are in place at all. This detection process would then be repeatedly applied for different regulatory minimums in different jurisdictions.

**Border post-processing and edge cases.** In our analysis, we are not analyzing the border segments themselves. Rather, we are classifying Census blocks around the segments as ones where a lot size regulation applies and ones where development is denser than the nearby minimum lot size requirement. Census block geographies may only cover areas that are all close to the segment, or stretch deeper away from the segment.

We use an iterative procedure to find tiles where a border segment was not detected, but should also still be fully contained in one district with one minimum lot size in effect. For each tile where a border segment is detected, we identify all neighboring interior cells where the 10th percentile of the lot size is above the bunching bin mapped to the initial tile. We do the same to expand the comparison area, where development is denser than the minimum lot size, to neighboring cells.<sup>7</sup>

<sup>&</sup>lt;sup>7</sup> For the remainder of the analysis, we run this neighbor detection step only once. However, we can iteratively apply this procedure to each newly assigned cell to expand the areas where we think a single minimum lot size regulation is in effect. This would let us detect census block groups or census tracts belonging to the same zoning district.

Another possibility is that a tile intersects with more than two zoning districts, so detecting a single linear segment on that tile is misleading about actual borders. In Appendix C, we describe an additional K-nearest neighbor classification model we run when a tile has multiple detected segments over different bunching bins. The KNN classifier, using additional parameters, define boundaries based on geocoded lot size data. As an output, areas within the tile are classified to only one of multiple areas with a minimum lot size.

# 3.2 Calibrating the detection procedure

Ahead of running the automated procedure, we make several choices: how large are the tiles used in local detection; how much misclassification error we tolerate when keeping borders, and other cases to handle. All these choices are governed by parameters we have listed in Section 3.1.

Table 1 lists out the key parameters detailed in the overview. Throughout our sample of cities, we set each tile to be 18 arcseconds in radius, or 36 arcseconds in diameter. The metric length of these tiles vary due to the Earth's curvature, but ranges from 700 meters in the northernmost continental U.S. cities to 1000 meters at the southernmost ones.

We do not filter out a large share of tiles before the detection process by using a low requirement for the number of lots whose sizes are around the bunching bins we process. However, many tiles are filtered out over the choice of the misclassification rate threshold,  $\overline{m_{err}} = 35\%$ . The parameters chosen for the KNN procedure are also intended to avoid generation of jagged borders overfitted on the assessor data.

As we extend our analysis, we will choose these calibrated parameters so they minimize detection of false negative borders: predicted border segments that do not appear on zoning maps, generated instead by developer decisions. We will fit and conduct a validation exercise for the procedure on the MAPC Zoning Atlas, a compilation of residential zoning borders for the Greater Boston metropolitan area. Our parameter choices aim to minimize segments unaligned with actual border segments, even if the procedure is not retracing zones' full borders.

### 3.3 Scope of procedure and summary statistics

We iterate the detection procedure across 120 of the largest Metropolitan Statistical Areas (MSAs) in the United States, where 241 million Americans live as of 2020. For each MSA where the data are available, we identify Census blocks in the 1980–2020 decennial censuses that have at least 70% of their area in a lot size treated area or the corresponding comparison

area. We also drop blocks that straddle a lot size boundary by having more than 7% of its area in both the treated and comparison areas. Our source for Census block shapes and statistics is the NHGIS (Manson et al., 2021)<sup>8</sup>

We produce as a result a repeated cross-section of demographic change around lot size borders, from 1980 to 2020.<sup>9</sup> Appendix Table A.1 shows the data cover 42 states, then compare coverage by taking means of block counts across Censuses. The most populated states — California, Florida and Texas — are also the most represented states in the data. Our procedure is likelier to skip over sections of Southern metros where strategic annexation makes for more complex interior regions of jurisdictions, while more likely to process all parts of jurisdictions in the Northeast and Midwest.

Table 2 shows summary statistics for blocks covering lot size treated areas, but also broken down according to four ranges of the areas' assigned minimum lot size. No range is dominated by a single minimum lot size value, though detected lot sizes are unlikely to below 5,000 or 6,000 square feet per unit. On average, areas with a larger minimum lot size have homes that are built later and are also located further from the metropolitan central business district (CBD). These trends are consistent with aggregate statistics on lot size adoption presented in Section 2. Large standard deviations around the two variables, however, point to idiosyncracies in area placement that are not explained fully by the negative density gradient in distance implied by monocentric city models (Duranton and Puga, 2015)

Finally, we sum together block-level counts to produce counts of residents inside each treatment area we define. The average area has 375 residents, with a standard deviation of 617 residents. As our treatment areas have similar radii but large minimum lot size areas are less dense, treatment areas with large minimum lot sizes can have as few as 93 people on average. These moments highlight how we exploit variation below the Census tract level, which on average contains 2,000–4,000 residents.

# 4 Empirical Strategy and Identification

Having defined our border sample, we employ border discontinuity designs to estimate racial disparities caused by lot size regulations. This research design is established in prior work (Turner, Haughwout and van der Klaauw (2014), Severen and Plantinga (2018), Song (2024),

<sup>&</sup>lt;sup>8</sup>We note that every MSA we process is in the NHGIS from 1990 onwards, but some MSAs lack 1980 data. NHGIS is still in the process of digitizing block shapes for every MSA in the 1980 Census, though they are not prone to releasing metro data where many constituent counties are incomplete.

<sup>&</sup>lt;sup>9</sup>The analysis dataset is not a panel dataset, because block borders do not stay constant between decades.

Schonholzer (2024)). Unlike those papers but in line with recent work (Kulka, Sood and Chiumenti, 2023), we are more interested in finding heterogeneous effects of the various minimum lot sizes adopted across America than an average effect over all border segments.

We specify a flexible statistical model that generate heterogeneous effects across different kinds of stratified samples in our data. Separate regressions on those samples identify separate effects of certain kinds of lot size regulations that alter surrounding residential development patterns.

## 4.1 Identifying Context-Specific Effects

Suppose that an individual *i* lives in and is surrounded by homes of lot sizes  $\{\ell\}_i$ , and we are interested in how minimum lot sizes affect a characteristic  $Y_i$ . The estimand

$$\mathbb{E}[Y_i | \min\{\ell\}_i \ge \underline{\ell}] - \mathbb{E}[Y_i | \operatorname{median}\{\ell\}_i = N], \quad \underline{\ell} > N,$$

is then an average treatment effect on the treated mapped to a policy-relevant question: how would  $Y_i$  differ if the surrounding residential context went from lot sizes no smaller than the regulatory minimum to being around N square feet? Though other conditions or demographics of the housing market individual i lives in matter, knowing this average effect informs the outcomes of a historical counterfactual: if an area in a city did not adopt a standard kind of minimum lot size and what was built was comparable to a higher density neighborhood elsewhere in the city.

In our empirical context, we have block level data  $Y_b$  instead of individual microdata. We define our *urban context-specific effects* over  $(\underline{\ell}, N)$  only slightly differently. Let **s** be a vector of points on border segments, where only one side gets treatment  $T_b = 1$  of a minimum lot size  $\underline{\ell}$ . Then

$$\beta(\underline{\ell}, N) = \mathbb{E}[Y_b(\mathbf{s}) | \min\{\ell | T_b = 1\}_{\mathbf{s}} \ge \underline{\ell}] - \mathbb{E}[Y_b(\mathbf{s}) | \operatorname{median}\{\ell | T_b = 1\}_{\mathbf{s}} = N].$$

To better understand this setup, we compare our effects to other statistical models around border discontinuity designs. One approach is found in Keele and Titiunik (2015), who also estimate border effects beyond an average effect. For each point on a particular border, they use a kernel weighing procedure to give more influence to observations close to a point. The collection of point-specific effects form a "treatment effect curve" in the space of geocoded coordinates. Our context borrows from this framework, but differs in our effect curve getting traced out in the space ( $\underline{\ell}$ , N). A direct consequence is that we may pool borders in different cities or states together to estimate a common effect, as long as the urban context on both sides of those borders look similar.

Another approach is a border discontinuity design with regression adjustment, like the economics papers of Severen and Plantinga (2018) and Schonholzer (2024). Those papers apply fixed effects and flexible covariates to make outcomes across cities and states comparable, at which point a single treatment effect is estimated from a pooled sample. As the next Section shows, our estimates also use fixed effects to ensure we use within-city variation that's not contaminated with between-city demographic differences. However, a single estimated effect does not have a clear map to all the possible counterfactuals worth considering for policy evaluation. Instead of imposing a restriction on how effects must vary across different minimum lot size reforms, we adopt more flexible approaches.

Where we can observe outcomes on blocks restricted by minimum lot sizes, the second term of this estimand is unobserved. By making a standard assumption on continuity of the regression function around the boundary, we identify the context-specific effects using surrounding block data outside of the minimum lot size zones, or where the lot size treatment  $T_b = 0$ :

$$\lim_{\mathbf{s}' \to \mathbf{s}} \mathbb{E} \Big[ Y_b(\mathbf{s}') \Big| \min\{\ell | T_b = 0\}_{\mathbf{s}'} \ge \underline{\ell} \Big] = \mathbb{E} \Big[ Y_b(\mathbf{s}) \Big| \min\{\ell | T_b = 0\}_{\mathbf{s}} \ge \underline{\ell} \Big]$$
$$\lim_{\mathbf{s}' \to \mathbf{s}} \mathbb{E} \Big[ Y_b(\mathbf{s}') \Big| \min\{\ell | T_b = 1\}_{\mathbf{s}'} \ge \underline{\ell} \Big] = \mathbb{E} \Big[ Y_b(\mathbf{s}) \Big| \min\{\ell | T_b = 1\}_{\mathbf{s}} \ge \underline{\ell} \Big].$$

As written, context-specific effects also form a curve over two continuous variables. To prioritize statistical power given the efficiency of our estimators, we estimate these effects in a "stepwise" manner. Rather than estimating the effect curve at each point, we estimate the same effect for different bin ranges of minimum lot size, interacted with different ranges of density.

### 4.2 Estimation Equation

Our underlying data consists of Census blocks from 1980 to 2020, where block boundaries are defined separately for each of the five Census waves. At this level of granularity, public tables using 100% of reported data show a limited number of responses in the short-form Census. Across all waves We observe total population and households; breakdowns by race, age and gender; as well as whether the resident owns or rents their housing unit.

We match each block b to its nearest lot size border segment, identified through the procedure in Section 3. The pairwise distance  $Dist_b$  is defined by the perpendicular distance from the block centroid to the segment. We only keep blocks within a certain distance from the border segment, or the blocks within the clustered tiles as described in Section 3.1. On one side, blocks are assigned a minimum lot size based on the detected value associated with the segment. On the other, blocks in the denser comparison area to the lot size area are assigned a development value N based on the median lot size of the hexagonal tile within which the property falls. <sup>10</sup>

With this filtered sample over blocks b, for each year t in the Census data we estimate the model:

$$Y_{bt} = \alpha_{j(b)t} + \beta^t \mathbf{1}[Dist_b \ge 0] + \eta^t_{-}Dist_b + \eta^t_{+}Dist_b \cdot \mathbf{1}[Dist_b \ge 0] + \varepsilon_{bt},$$

where in the baseline we apply zoning jurisdiction-year fixed effects  $a_{j(b)t}$ , though other fixed effects are also used for robustness. We difference away local government traits that could explain sorting between cities to reduce bias, but also to increase estimate precision. To handle spatial autocorrelation in other demographic trends causing suburban change, we also cluster errors at the county level.

By construction, there is an upper bound for  $Dist_b$  in the sample, as much as 1 kilometer within some jurisdictions. We use less than the full sample by following the data-driven bandwidth selection procedure in Calonico, Cattaneo and Titiunik (2014). The estimation sample is trimmed to a smaller interval around the border where conditional expectations of the outcome look the most linear. In most specifications, the interval is between 200 to 350 meters on each side. The terms  $\eta_Dist_b + \eta_Dist_b$  then represent a nonparametric way to control for trends around the border.

As specified, our estimation equation can be fit using variation around all lot size borders in our sample, no matter the urban context. To estimate context-specific effects, we approximate the full curve of these effects with stratified samples. The stratification involves a further step at the start: we keep only information around lot size borders where the regulatory treatment on one side is in a range of values, then where the difference in median lot size on the other side with the regulatory minimum is in a range. We refer to the median lot size over properties in the comparison group as the group's "density."

In our main results, we focus on three of these stratified samples:

1. The *high density sample*, where the regulatory minimum lot size is no larger than 6,000 square feet but the difference with the comparison group density is at least 2,000 square

 $<sup>^{10}</sup>$ In other words, the "surrounding residential context" referred to in the previous section includes units of at most radius *R* away from any particular lot.

feet.

- 2. The *medium density sample*, where the regulatory minimum lot size is between 6,000 and 11,000 square feet ( $\sim 1/4$  acre) but the difference with the comparison group density is no more than 4,000 square feet.
- 3. The *large density shift sample*, where the regulatory minimum lot size is between 6,000 and 11,000 square feet but the difference with the comparison group density is at least 4,000 square feet.

The blocks in these samples make up around 52% of all blocks in our data, as of 2020. <sup>11</sup> In Table 3, we take simple differences in means over two of these samples to observe differences in neighborhood composition as we move away from the border. Single-family homes in treated blocks are only built 5–6 years later than those in comparison blocks, on average. However, even in 1980 a comparison block had 8-13 percentage points more residents in a racial minority on average than a treated block. Tenure differences were also present, with an average difference of 16-17 percentage points.

These differences between treated and comparison blocks are significant, but the standard deviations of the covariates are also noisy. We can draw two conclusions from Table 3. A border discontinuity design is preferred over event studies using the entire sample, because historical disparities could confound later estimates. Furthermore, the high variability of the raw data justifies using fixed effects when pooling the sample together.

# 4.3 Are Covariates Similar Across Borders?

Formally, a border discontinuity design identifies the marginal effect of restrictive lot sizes if potential outcomes are *continuous throughout the border* deciding where the regulation cuts off. In our empirical context, we are more assured this assumption holds if we do not see discontinuities around the boundary in other covariates that can influence residential location of racial minorities.

One concern with our design is that we observe outcomes only from 1980 onwards, due to data limitations. The years for which Census data are available are all after the adoption of minimum lot sizes in most jurisdictions, as described in Section 2. By 1980, it could be that residential sorting on income across lot size borders caused denser areas in the comparison blocks

<sup>&</sup>lt;sup>11</sup>Appendix Figure B.2 demonstrates this with a heatmap density plot, which show minimum lot size ranges fully interacted with ranges of differences with comparison group density. Much of the remaining sample is in areas with small lot sizes and small differences with the comparison group, or where one side has a minimum lot size of over 11,000 square feet.

to have more units available for rent. The comparison blocks may also see more redevelopment over time, or have different composition by age than the treated blocks. These shifts in housing tenure or in other local housing conditions can affect racial minorities' location choice once more of them can afford suburban living (Resseger (2022), Furth (2022))

We check if we can rule out these feedback mechanisms, where lot size borders matter only in how they caused changes in neighborhood amenities and affordability other than allowed density. Table 4 estimates covariate discontinuities at the border for two samples, the high density and large density shift samples. Our measure of local housing tenure is the share of rental units in a block, available through the Census. We also include two moments of the age distribution: the shares of residents under 18 or over 65. Looking at the third row that estimates effects only over 1980 Census data, we see point estimates on the rental unit share that are negative but statistically insignificant at a 90% level. More reassuringly, disparities in rental units or in the age distribution are not statistically significant over time after 1980. Point estimates for age distribution outcomes are also small, often less than 1 percentage point, relative to the insignificant rental unit share results.<sup>12</sup>

In our research design, we already use variation only within jurisdictions and fixed effects to control for the possibility of correlations between which cities adopt certain minimum lot sizes and their demographics. Even within cities, Table 3 shows blocks further away from the lot size border may differ to large degrees in housing unit tenure and demographics. There is less evidence that the differences still hold in a discontinuous way right around the lot size border, which justifies our border discontinuity design.

We plan to conduct additional checks for the presence of other covariate discontinuities. As in Kulka, Sood and Chiumenti (2023), a lack of discontinuities in land elevation or natural amenities around the border affirms the border segments we use did not strategically separate out parcels by land quality. In Section 5.3, we also further adjust our main estimates based on whether housing stock age is confounded with the adoption of certain minimum lot sizes over others.

<sup>&</sup>lt;sup>12</sup>Appendix Table A.3, which we discuss more in a later section, shows similar lack of discontinuities for the medium density sample.

# 5 Results on Racial Disparities

### 5.1 Results For Pooled Versus Context-Specific Effects

We run the border discontinuity design, as specified in Section 4.2, around all minimum lot size segments we identify. In this subsection and in what follows, our measures of racial diversity will be block-level shares of a specific racial group m, denoted  $Share_{bt}^{m}$ , or the share of racial minorities  $Share_{bt}$ , defined as total population excluding non-Hispanic white residents.

Table 5 presents separate effects for three years: two recent Census years (2020 and 2010) and the earliest year in our sample (1980). As of the latest data available, we estimate small racial disparities for areas treated with a more restrictive minimum lot size than the surround-ing comparison area. In the baseline specification with jurisdiction fixed effects, there is on average 0.1 percentage points more nonwhite residents in the treated area than in what is compared. This positive effect is statistically insigificant at the 95% level.

Other 95% significant disparities are found with a specification with more granular fixed effects, defined over each separate border segment, and with Black American shares as the outcome. In 2020, however, these effects are not important in magnitude, with a decline of at most 0.8 percentage points. We also do not find large effects going back in time, when metropolitan segregation was higher (Cutler, Glaeser and Vigdor, 1999). The greatest disparity in magnitude we estimate is for nonwhite share in 2010, with a decline of 1.7 percentage points across the minimum lot size border.

In contrast to these results on the pooled sample, we rerun the design filtered around lot size discontinuities in the high density sample. While we also check densities based on observable built units, the difference in allowable density around these borders is between 2,000 to 6,000 square feet. As suggested by moments in the second to left column of Table 2, these residential areas are closer to the urban core and reflect units built to satisfy household demand closer to the start of postwar suburbanization.

Figure 3, computed over 2020 Census data, nevertheless show sizable racial disparities around the border. In the latest data, these residential areas have a "majority-minority" population, with mean nonwhite share of 60%. Panel (a) plots an estimated disparity from our nonparametric model of 2.8 percentage points, or 5 percent of baseline shares. We also observe that the nonwhite share continues to fall as we increase distance, reflecting movement deeper into the lot size restricted blocks.

To verify how much of this regulatory shift is reflected in built density, Panel (b) runs the same specification but changing the outcome. We estimate the effect on block-level housing

unit density, dividing occupied housing units in Census tables by the block area in square kilometers. We estimate that, at the border, the comparison group density is 2270 occupied units per square kilometer. On the other side of the lot size border segment, density drops by 370 units/km<sup>2</sup> to 1904 units/km<sup>2</sup>.

We can make back-of-the-envelope calculations to infer the change in density on residential land induced by minimum lot size regulations in this sample. This calculation is imprecise, as not all land in the block is for residential use; some of the land will be used for streets or for commercial use. We assume for simplicity that 24% of the land is used for street space, based off of recent estimates in Guerra, Duranton and Ma (2024). The average shift in realized density at the border is then a lot size reduction of 694 square feet. Using forecasted lot sizes around the border, this is a shift in dwelling units per acre of 12.1 - 10.1 = 2.0 DUPAC.

We present results for three measures of racial diversity, across two samples, in Table 6. The first row of the Table represents estimates on 2020 Census data. The leftmost result reflects the border discontinuity estimate visualized in Figure 3, panel (a): -2.8 percentage points, at a p-value p = 0.063. When the outcome is specifically disparities in the Black residential share, we find an effect of -3.4 percentage points that is significant at the 95% level. This effect is 17% of the baseline rate of 19.6% Black residents.

Towards the right of Table 6, we also present results on the high density sample. Running the border design on housing unit density, we find that the average drop in density across the border in this sample is around 1150 square feet, or a shift in dwelling units per acre of 9.4 - 7.6 = 1.8 DUPAC. In 2020, we find racial disparities comparable in magnitude to what we found in the high density sample: however, the standard errors are larger and the null hypothesis cannot be rejected. As we note in more detail in the next Section, racial disparities at the border are also large in 2010 and are statistically significant there. <sup>13</sup>

Finally, in the third to left and rightmost columns we break out the Asian share at the block level as an outcome. On average, the Census data used in Section 2 shows Asian Americans have higher median incomes. In recent correspondence studies testing discrimination in rental markets, there is conflicting evidence on whether Asian Americans are steered into certain neighborhoods (Turner and Ross (2003), Christensen and Timmins (2022)). In our discontinuity estimates, we do not any statistically significant disparities caused by lot size borders on the residential location of Asian Americans. Point estimates are also small in magnitude, no

<sup>&</sup>lt;sup>13</sup>Between 2010 and 2020, the Census Bureau also changed a disclosure avoidance algorithm, which adjusts block-level counts for privacy reasons (Asquith et al., 2022). The 2020 Census vintage more explicitly adds "noise injection" to each block, shifting both the denominator of the outcome variable (population) and the numerator (race-specific counts). This source of intentional measurement error could bias estimates and confidence intervals compared to the 2010 results.

greater than a fall of 0.8 percentage points in 2020.

While Table 6 presents two stratified samples that appear to cause racial disparities, there are numerous other configurations involving the rest of our sample that cannot find significant evidence. One example is the medium density sample defined in Section 4.2, altogether comprising 36% of our sample. In Appendix Table A.2, the leftmost three columns show that in 2020, estimated racial disparities are all statistically insignificant. Point estimates even suggest racial minorities are more likely to move into the lot restricted neighborhoods. Estimates for 2010 show disparities statistically significant at the 95% level, but at 2 percentage points they are reduced in magnitude compared to earlier samples.

Table A.2 also features, in the three rightmost columns, a sample of areas that have minimum lot sizes detected to be between 11,000 to 22,000 square feet, compared to surrounding development with density increases of no more than 6,000 square feet. This sample is analogous to the medium density sample in how we put an upper bound on density shifts, but using larger minimum lot size districts in the treated areas. Using multiple measures of racial diversity — block-level shares of all racial minorities and block-level shares of Black Americans — we find small effects. Over this second sample, we cannot reject the null hypothesis of zero racial disparities around regulatory borders.

A primary reason for these null results is that even if the comparison group overall is denser than the minimum lot size districts being compared to, that gap in density no longer exists when limited to both sides of the regulatory border. We run the same border discontinuity design estimate on Census block-level density data to estimate the density function. For the medium density sample, we estimate a density of 1240 units/km<sup>2</sup> on the regulated side and a density of 1250 units/km<sup>2</sup> on the comparison side.<sup>14</sup> When most lot size border segments in this sample did not deviate much from development already built up on the other side of the border, our design is too underpowered to conclude any racial diversity effects of implementing minimum lot size regulations.

To further show how racial disparities are not large when one side has minimum lot sizes above 11,000 square feet, we plot effects along a heat map structure in Appendix Figure B.3 Using block-level Black shares as the racial diversity outcome, we visualize discontinuity estimates over 14 possible subsamples. Descending down the Y axis, the subsamples have larger minimum lot sizes as the treated areas. Moving rightwards along the X axis, the subsamples have comparison groups whose densities get higher compared to the treated areas. To illustrate our point, we note that the row corresponding to samples with 11,000 to 22,000 square

 $<sup>^{14}</sup>$ For the second sample in Table A.2, the estimated density is 835 units/km<sup>2</sup> on the regulated side and 780 units/km<sup>2</sup> on the comparison side.

feet treated areas have negative point estimates close to zero, or positive estimates suggesting developments where minimum lot sizes bind are more Black.

## 5.2 Dynamics of Racial Disparities

Analyzing one year of the most recent data show whether minimum lot sizes matter for racial disparities today. It is uninformative, however, about how these disparities compare to the past. One possibility is that racial disparities were even larger in past decades, when suburbanization of racial minorities had only begun. As absolute income levels for racial minorities grow, they choose to spend more on housing consumption and are more likely to consider less dense homes on the other side of a minimum lot size border.

Figure 4 provides estimates from border discontinuities over time for the high density sample analyzed in Section 5.1. Within this sample, we do not find results supportive of racial disparities getting closed. On the contrary, point estimates of racial minority disparities grow from 2000 onwards. Noisy point estimates from 1980 to 2000 suggest either persistence or convergence, but in 2010 the disparities grow to 6.7 percentage points around the lot size borders, or 14 percent of a 49% baseline share.

The second and third rows of Table 6 point out estimates of racial disparities for two past years for multiple outcomes. The leftmost column of results pick out border estimates covered in more detail in Figures 3, panel (a) and 4.<sup>15</sup> The second and third columns show that over the same sample, disparities around Black residential shares follow similar dynamics to those with all racial minorities. Furthermore, there were no disparities in Asian residential shares in previous decades as well.

As we are estimating context-specific effects, the dynamics of racial disparities could also differ depending on the context. In the rightmost three columns, we estimate dynamic effects over the large density shift sample. When the outcome is either the share of all racial minorities or the share of Black Americans, we find similar patterns to results in the high-density sample: by 2010, point estimates of racial disparities around the sample's regulatory borders are similar in magnitude as in 1980, or even greater.

In Appendix Table A.2, we check if there were greater racial disparities in previous decades for the additional two lower density samples. We cannot reject the null that, in 1980, there were no racial disparities around regulatory borders for the additional samples either.

<sup>&</sup>lt;sup>15</sup>Panel (a) of Appendix Figure B visualizes the border discontinuity for the racial minority share in 1980, like with 3 for 2020. Panel (b) visualizes the border discontinuity for a confounder discussed in Section 4.3, the share of rental units at the Census block level.

### 5.3 Results on Different Housing Vintages

Though our context specific effects offer evidence that minimum lot size regulations can have varying impacts at the margin, up to now we have not modelled heterogeneity by age of the housing stock. In Section 3.1, summary statistics across samples have shown high density environments have homes built earlier. Not adjusting for age could also confound our main estimates and bias us toward evidence of disparities.

To see if this hypothesis is borne in the data, we stratify the three samples in Section 4.2, covering different urban contexts, based on the year built of homes being compared. For blocks in the treated or comparison areas around a lot size border, we further classify them according to the median year built of homes in the hexagonal tile from Section 3 they are matched to. We define a *contemporary housing sample* as areas where both sides of the lot size border have homes with median year built after 1980. The remaining tiles are referred to as the *postwar sample*.

Our choice of 1980 as a cutoff year for dividing the sample is first motivated by the dynamics of lot size adoption. As estimates in Cui (2024) find that jurisdictions slow down in adoption of minimum lot sizes in the 1970s, blocks built up after 1980 are less likely to be areas already built up when the jurisdictions first planned these regulations. We are then less concerned the border segments for these blocks were deliberately drawn to keep a set of more valuable, larger lot developments in the same residential zone.

Additionally, full national coverage among our Census block data go back as early as 1990. If we believe racial disparity effects of lot size regulations are dynamic as a function of housing stock age, Estimating specific effects across Census years for the contemporary sample backs out a different set of dynamic effects than it would for the housing stock. The estimates on the contemporary sample reflect effects of lot size design while the housing stock is still new; estimates on the postwar sample reflect effects of lot size design when the housing stock has aged.

Over  $2 \times 3 = 6$  samples stratified by urban context and housing stock age, we adopt a more parametric specification to estimate a boundary discontinuity design. Averaged over urban context by time, the contemporary sample is 41% the size of the source sample: we thus have fewer observations to efficiently estimate nonparametric effects. For block *t* in time *t*, we estimate the specification

$$Y_{bt} = \alpha_{p(b)t} + \beta^t \mathbf{1}[Dist_b \ge 0] + \eta^t_{-}Dist_b + \eta^t_{+}Dist_b \cdot \mathbf{1}[Dist_b \ge 0] + \varepsilon_{bt},$$

which deviates from the previous specification in two ways. First, we no longer use a datadriven bandwidth and look at all blocks with a distance of 500 meters from the lot size border. Second, we use fixed effects over all blocks around a border segment in our sample.<sup>16</sup>

We are interested in estimating  $\beta^t$  separately, checking whether the effects are small or statistically insignificant once they are estimated on just the contemporary sample. We are also interested in comparing how  $\beta^t$  changes across time in different ways between the postwar versus contemporary samples. Figure 5 plot these estimates and 95% confidence intervals for two outcomes measuring racial diversity. In each panel, we fix a sample stratified by urban context. Then, we estimate three year-specific effects over subsamples by housing stock age.

Our first conclusion is that effects on the contemporary sample are not small. Point estimates for these newer developments mostly point to larger or comparable magnitudes to those in the postwar samples. We notably find housing stock age matters for the presence of racial disparities around borders in the medium density sample — a sample with more observations than the other two combined. In the contemporary medium density sample and as of 2020, blocks across the lot size border have 2.8 percentage points lower racial minority shares, as well as 1.0 percentage points lower Black resident shares.

Our second conclusion is that moving from earlier decades to the present, the dynamics of effects between the samples do not differ much from each other. For the postwar sample of homes mainly built before 1980, effects estimated in 1990 do not significantly deviate from effects in 2020. This is despite greater suburbanization over those decades, such that by 2020 the marginal suburban entrant is likelier to be part of a racial minority with real incomes close to white residents buying those homes when first built.

We also do not find noticeable convergence of effects to null effects in the contemporary sample, apart from racial minority shares in the large density shift sample in 2020. The insubstantial racial disparities estimates for older homes in the medium density sample suggests, when lot size regulations are not altering surrounding density to a large extent, short-run racial disparities could form and then disappear disappear as the neighborhood housing stock ages.

Overall, Figure 5 offers another check that racial disparities around lot size borders are not caused by other compositional effects of the housing stock. Changes in allowable density attributed to lot size regulations can alter where racial minorities locate within cities in sizable ways. Surrounding urban context, which determines how much a minimum lot size in the code actually changes the density of market driven ndevelopment, affects whether these racial

<sup>&</sup>lt;sup>16</sup>Existing studies using the border discontinuity design often refer to "border pair fixed effects." The only difference with our design is that we might estimate separate effects at different parts of a single border separating two residential zones, because we detected multiple segments along that border.

disparities disappear over time or have more persistence.

# 6 Discussion

### 6.1 Contextualizing Results With Mechanisms

In this paper, we have focused on flexibly estimating how the presence of minimum lot size regulations caused changes in an equilibrium outcome: the magnitude of racial disparities in residential decisions around the regulatory border. The ways in which the regulations caused changes in the regulated areas' characteristics, relative to an unregulated counterfactual, is beyond the paper's scope. However, we use this section to discuss possible mechanisms consistent with our findings.

To rationalize racial disparities, we can model residential location choice between racial and ethnic groups g in a random utility manner, following Kuminoff, Smith and Timmins (2013) and Diamond (2016). Suppose household i of group g and income y chooses between neighborhoods  $\ell$ , so household members receive a random utility value in  $\ell$ :

$$V_{i\ell gy} = \delta_{\ell} + \beta^{h}_{igy} h_{\ell} + \beta^{p}_{igy} p_{\ell} + X'_{\ell} \Gamma_{igy} + \overline{\xi}_{\ell} + \varepsilon_{i\ell gy}$$

where each neighborhood has housing quality  $h_{\ell}$ , price level of housing  $p_{\ell}$  and other local amenities  $X_{\ell}$ . In the samples we have analyzed around regualtory borders, lot size regulated areas are mandated to have higher  $h_{\ell}$  than their surroundings. Holding all characteristics other than h constant, the lot size requirement induces racial disparities based on the price elasticity of demand for housing between different racial groups. As Black Americans in history have had lagging mean household incomes to other groups, they could have more inelastic demand at their mean income levels than those of higher-income White Americans.<sup>17</sup>

However, our findings show that racial disparities persist around dense development and relatively small minimum lot sizes. The disparities are less apparent between large lot size areas and surrounding dense development — where sharp changes in  $h_{\ell}$  are even larger. When effects are lasting through to the 21st Century, where differences in  $h_{\ell}$  induced by minimum lot sizes are not large compared to the full choice set of American households, we conjecture other mechanisms not based on the elasticities  $\beta^h$  are at work. The changes to the neighborhood caused by the lot size regulation also affects amenities  $X_{\ell}$ , mean utility  $\delta_{\ell}$  and more.

<sup>&</sup>lt;sup>17</sup>Alternatively, Black Americans may have greater preferences for density than White Americans and other racial groups. This would be modelled as heterogeneity in the elasticities  $\beta^h$  by type.

The changes could also be heterogeneous depending on the urban context, nor must racial disparities arise from greater income gaps between areas.

In one scenario, high income households who choose a high density suburban neighborhood also strongly prefers the demographic composition and character of lot size restricted areas. That is, a certain group g values  $X_{\ell}$  highly. An observable implication would be that the racial disparities in this urban context is paired with growing income disparities around the regulatory border. In another, incumbents who first bought into the lot size restricted developments value local amenities so much that they refuse to sell their properties and leave. Since incumbents to neighborhoods are less likely to be racial minorities, racial disparities persist but due to changes in  $X_{\ell}$  and higher prices  $p_{\ell}$  resulting from limited local supply. Instead of growing income disparities, the testable implication here is a sharp drop in housing turnover rates on one side of the regulatory border.

We cannot as of yet distinguish between the various mechanisms, but believe the compounding impact of these mechanisms explain how large effects are to other work in the literature. We analyzed four other papers that use a border discontinuity design and considers as an outcome the Black share of Census blocks or block groups, the next smallest Census geography. The policy intervention varying across borders that they study are either historical interventions that are not legally enforceable (Aaronson, Hartley and Mazumder (2021), Sood and Ehrman-Solberg (2024)) or remain in effect (Monarrez and Schönholzer (2023), Resseger (2022)) All estimates from these designs have a partial equilibrium interpretation: deriving the average treatment effect on areas receiving the intervention, relative to other local neighborhoods.

In Appendix Table A.4, we show our comparable estimates — racial disparities in the Black American share in 2010 — are between 4 and 5 percentage points. These are comparable to the disparities around local government borders in (Monarrez and Schönholzer, 2023). While all the mechanisms discussed above also follow if neighborhoods differ on a local public good instead of lot size restrictions, that estimated disparities are similar across both types of sharp policy shifts suggests density zoning is worth studying for its consequences as much as local provision of public goods.

Our estimates of Black residential disparities are also larger than the post-2010 effects of the two cited historical interventions. Both papers study a past constraint on residential choice affecting racial minorities, whether it is unequal credit access (Aaronson, Hartley and Mazumder, 2021) or legal covenants banning sales (Sood and Ehrman-Solberg, 2024). It is possible that even after those historical constraints were not enforced, they still changed perceived neighbor-

hood characteristics enough to have persistent impact on modern day residential choices. That said, the greater magnitude of our estimates suggest lot size regulations were more impactful at altering those characteristics.<sup>18</sup>

## 6.2 Policy Implications for Regulatory Reforms and for Fair Housing

Our results have a number of implications for policy. First, many state and local governments are considering land use reforms to remove inefficient or unfair barriers to housing production that are, at least in part, responsible for the housing affordability crisis across the nation. At least fourteen states have now adopted significant reforms that seek to cabin local governments' ability to limit density, and many cities have revised their zoning ordinances to allow denser development as well.

Among the reforms are specific restraints on minimum lot size requirements to allow accessory dwelling units such as backyard cottages or over-the-garage apartments to be built on lot that already has one residential unit (Cal. A.B. 68, 2019-20 Leg., §§1-2. 2019). Similarly, some reforms allow existing lots to be split into two or more lots, thereby reducing the lot size by half or more (Cal. S.B. 9, 2021-22 Leg., §1. 2021). Others require local governments to allow "gentle density" — such as duplexes and triplexes — to be built on areas zoned for (and applying minimum lot sizes to) single family homes (Baca, McAnaney and Schuetz (2019); Been, Zhang and Kazis (2023); Maine H. Paper 1489, 2022)). In each of those examples, information about the effects that lot size restrictions have on racial diversity within the neighborhood and in the jurisdiction could guide the choices legislatures are making about what whether to allow local governments to impose any lot size minimums at all, and if so, which size restrictions are least likely to cause racial disparities among new movers into the area.

Many jurisdictions are grappling with how to add density to low density neighborhoods, amid controversy over the effects that the additional density will have to the quality of life within those neighborhoods. Our findings can also help local governments manage those transitions by paying attention to the way in which differences between the densities in areas subject to a particular lot size and those in adjacent neighborhoods affect the role the lot size minimums play in discouraging racial diversity.

Many local governments are undertaking (with some states mandating) equity assessments of their existing land use regulations. Our findings should help guide those jurisdictions to pay attention to the exclusionary effects of lot size minimums, and to revise or eliminate those

<sup>&</sup>lt;sup>18</sup>Sood and Ehrman-Solberg (2024) remarks as much that on average, development in Hennepin County, MN with a racial covenant did not have much larger lot sizes compared to surrounding development.

minimums where appropriate.

Finally, our findings may be helpful to litigants seeking to establish that lot size minimums have contemporary exclusionary effects and may thereby violate the Fair Housing Act. The Supreme Court has demanded that those challenging land use regulations point to a specific policy and prove "robust causality" between that policy and disparate effects by race. That standard is a difficult one to meet, but our evidence can be helpful in establishing the direct causal relationship between the specific lot size minimums under review and disparities in racial composition of the surrounding neighborhood.

# 7 Conclusion

Our paper develops a procedure to create a novel dataset of minimum lot size regulations. The resulting data show where local governments applied the regulations and where the ensuing development deviated the most from the density of less regulated adjacent development. The data records rich heterogeneity in how these zoning regulations alter the urban context, which zoning ordinances and maps cannot capture in full.

We use these data to produce new findings about how minimum lot size regulations, though planned decades in the past, persistently shapes the geography of U.S. racial diversity. First, in higher density areas analogous to the first postwar suburbs, lot size regulations decrease density by 2 units per acre on average and cause sizable declines in racial diversity. Second, we do not find large point estimates or conclusive effects on racial diversity when the minimum lot size are "large" — above a quarter acre. Finally, the effects we find are sizable even across samples where the age of the housing stock are decades apart from each other.

By combining big data on regulations with causal inference techniques, we provide evidence on which specific regulations among many matter for a policy objective: increasing racial integration into more advantaged communities. Our approach of estimating context-specific effects is one way to model heterogeneous treatment effects across a class of regulations.

When the dataset created in this paper and Cui (2024) are combined, the result is a detailed atlas of minimum lot size regulations within American jurisdictions. Using the data, we can rank many U.S. cities based on how stratified their residents are by different degrees of density zoning, as well as identify which cities began planning for density restrictions ahead of others. Using the data, we can study in great detail how planning decisions in the past had downstream effects on local public goods investment, real estate markets and the barriers local decisionmaking had posed to the development of more equitable cities.

# References

- Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder. 2021. "The Effects of the 1930s HOLC "Redlining" Maps." *American Economic Journal: Economic Policy*, 13(4): 355–392.
- Advisory Committee on Zoning. 1926. "A Standard State Zoning Enabling Act: Under Which Municipalities May Adopt Zoning Regulations." Washington.
- Ananat, Elizabeth Oltmans. 2011. "The Wrong Side(s) of the Tracks: The Causal Effects of Racial Segregation on Urban Poverty and Inequality." *American Economic Journal: Applied Economics*, 3(2): 34–66.
- Asquith, Brian, Brad Hershbein, Tracy Kugler, Shane Reed, Steven Ruggles, Jonathan Schroeder, Steve Yesiltepe, and David Van Riper. 2022. "Assessing the Impact of Differential Privacy on Measures of Population and Racial Residential Segregation." *Harvard Data Science Review*, , (Special Issue 2).
- Baca, Alex, Patrick McAnaney, and Jenny Schuetz. 2019. ""Gentle" Density Can Save Our Neighborhoods." https://www.brookings.edu/articles/gentle-density-can-save-our-neighborhoods/.
- **Bartik, Alexander, Arpit Gupta, and Daniel Milo.** 2024. "The Costs of Housing Regulation: Evidence From Generative Regulatory Measurement."
- **Bartik, Alexander W., and Evan Mast.** 2023. "Black Suburbanization: Causes and Consequences of a Transformation of American Cities." W.E. Upjohn Institute.
- Baum-Snow, Nathaniel. 2007. "Did Highways Cause Suburbanization?"." The Quarterly Journal of Economics, 122(2): 775–805.
- Been, Vicki, Helen Zhang, and Noah Kazis. 2023. "Allowing More and Different Types of Housing."
- Bergman, Peter, Raj Chetty, Stefanie DeLuca, Nathaniel Hendren, Lawrence F. Katz, and Christopher Palmer. 2024. "Creating Moves to Opportunity: Experimental Evidence on Barriers to Neighborhood Choice." *American Economic Review*, 114(5): 1281–1337.
- **Boustan, Leah Platt.** 2010. "Was Postwar Suburbanization "White Flight"? Evidence from the Black Migration\*." *The Quarterly Journal of Economics*, 125(1): 417–443.
- **Bronin, Sara C., Scott Markley, Aline Fader, and Evan Derickson.** 2023. "How to Make a Zoning Atlas 2.0: The Official Methodology of the National Zoning Atlas."
- **Caetano, Gregorio, and Vikram Maheshri.** 2023. "A Unified Empirical Framework to Study Segregation."
- **Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik.** 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." *Econometrica*, 82(6): 2295–2326.

- **Card, David, Alexandre Mas, and Jesse Rothstein.** 2008. "Tipping and the Dynamics of Segregation." *The Quarterly Journal of Economics*, 123(1): 177–218.
- Christensen, Peter, and Christopher Timmins. 2022. "Sorting or Steering: The Effects of Housing Discrimination on Neighborhood Choice." *Journal of Political Economy*, 130(8): 2110–2163.
- **Chyn, Eric.** 2018. "Moved to Opportunity: The Long-Run Effects of Public Housing Demolition on Children." *American Economic Review*, 108(10): 3028–3056.
- **Cui, Tianfang.** 2024. "Did Race Fence Off The American City? The Great Migration and the Evolution of Exclusionary Zoning."
- Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor. 1999. "The Rise and Decline of the American Ghetto." *Journal of Political Economy*, 107(3): 455–506.
- **Davis, Morris A., Jesse Gregory, and Daniel A. Hartley.** 2023. "Preferences over the Racial Composition of Neighborhoods: Estimates and Implications."
- **Diamond, Rebecca.** 2016. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000." *American Economic Review*, 106(3): 479–524.
- **Duranton, Gilles, and Diego Puga.** 2015. "Chapter 8 Urban Land Use." In *Handbook of Regional and Urban Economics*. Vol. 5 of *Handbook of Regional and Urban Economics*, , ed. Gilles Duranton, J. Vernon Henderson and William C. Strange, 467–560. Elsevier.
- Furth, Salim. 2022. "Single-Family Zoning and Race: Evidence from the Twin Cities."
- Gallagher, Ryan, Allison Shertzer, and Tate Twinam. 2024. "Zoning and the American Suburb."
- **Gardner, Charles.** 2023. "Urban Minimum Lot Sizes: Their Background, Effects, and Avenues to Reform | Mercatus Center." *https://www.mercatus.org/research/policy-briefs/urban-minimum-lot-sizes-their-background-effects-and-avenues-reform*.
- **Gardner, Charles.** 2024. "Cutting Zoning Down to Size: Reevaluating the Legal Vulnerability of Urban Minimum Lot Sizes." *San Diego Law Review*, 61(2): 231.
- **Glaeser, Edward L., and Jacob L. Vigdor.** 2012. "The End of the Segregated Century: Racial Separation in America's Neighborhoods, 1890-2010."
- **Guerra, Erick, Gilles Duranton, and Xinyu Ma.** 2024. "Urban Roadway in America: The Amount, Extent, and Value."
- **Gyourko, Joseph, and Sean McCulloch.** 2023. "Minimum Lot Size Restrictions: Impacts on Urban Form and House Price at the Border."
- Keele, Luke J., and Rocío Titiunik. 2015. "Geographic Boundaries as Regression Discontinuities." *Political Analysis*, 23(1): 127–155.

- **Kulka, Amrita, Aradhya Sood, and Nicholas Chiumenti.** 2023. "Under the (Neighbor)Hood: Understanding Interactions Among Zoning Regulations."
- Kuminoff, Nicolai V., V. Kerry Smith, and Christopher Timmins. 2013. "The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets." *Journal of Economic Literature*, 51(4): 1007–1062.
- Macek, James. 2024. "Housing Regulation and Neighborhood Sorting across the United States."
- Maheshri, Vikram, and Kenneth Whaley. 2024. "Boundaries Generate Discontinuities in the Urban Landscape."
- Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. 2021. *IPUMS National Historical Geographic Information System: Version 16.0 [Dataset]*. Minneapolis, MN:IPUMS.
- Monarrez, Tomás, and David Schönholzer. 2023. "Dividing Lines: Racial Segregation across Local Government Boundaries." *Journal of Economic Literature*, 61(3): 863–887.
- **Resseger, Matthew.** 2022. "The Impact of Land Use Regulation on Racial Segregation: Evidence from Massachusetts Zoning Borders."
- Rothstein, Richard. 2017. The Color of Law: A Forgotten History of How Our Government Segregated America. . First edition. ed., W.W. Norton.
- Schonholzer, David. 2024. "Measuring Preferences for Local Governments."
- **Severen, Christopher, and Andrew J. Plantinga.** 2018. "Land-Use Regulations, Property Values, and Rents: Decomposing the Effects of the California Coastal Act." *Journal of Urban Economics*, 107(C): 65–78.
- Shertzer, Allison, Tate Twinam, and Randall P. Walsh. 2022. "Zoning and Segregation in Urban Economic History." *Regional Science and Urban Economics*, 94(C).
- Song, Jaehee. 2024. "The Effects of Residential Zoning in U.S. Housing Markets."
- **Sood, Aradhya, and Kevin Ehrman-Solberg.** 2024. "The Long Shadow of Housing Discrimination: Evidence from Racial Covenants."
- **Trounstine, Jessica.** 2020. "The Geography of Inequality: How Land Use Regulation Produces Segregation." *American Political Science Review*, 114(2): 443–455.
- **Turner, Margery, and Stephen Ross.** 2003. "Discrimination in Metropolitan Housing Markets Phase II: Asians and Pacific Islanders." *Economics Working Papers*.
- Turner, Matthew A., Andrew Haughwout, and Wilbert van der Klaauw. 2014. "Land Use Regulation and Welfare." *Econometrica*, 82(4): 1341–1403.





(a) Measured Adoption Rates of Minimum Lot Size Regulations

*Notes:* Panel (a) of this Figure visualizes estimates of minimum lot size adoption from Cui (2024) among U.S. jurisdictions with a population over 5,000. The time series plots both adoption of any minimum lot sizes, along with initial adoption of a zone with lot sizes over 7,500 square feet. Panels (b) and (c) report aggregate trends calculated from Census products. In both panels, the definition of "racial minority" is all residents not identifying as non-Hispanic White Americans. *Sources:* Calculations from 1970–2020 NHGIS Tables (Manson et al., 2021)), Census Historical Income Tables (?), Table H-5, and CoreLogic Tax Records.

# (a) Obtaining where to search for lot size discontinuities

Figure 2: Illustration of algorithm detecting lot size discontinuities



*Notes:* Using multiple panels, this figure illustrates the workflow to detect lot size discontinuities for an example minimum lot size in a jurisdiction. The example is the 30,000 square foot minimum lot size in Lower Merion Township, PA. The illustrated procedure is then looped over multiple jurisdictions and their lot size regulations. Details of the algorithm are written in Section 3. *Sources:* Calculations from CoreLogic Tax Records.



Figure 3: Nonparametric effects of minimum lot sizes in high-density urban contexts

*Notes:* This figure presents border discontinuity effects on data from 2020, estimated across stratified samples of lot size segments. Effects are estimated from the fixed effects model

$$Y_{bt} = \alpha_{i(b)t} + \beta^t \mathbf{1}[Dist_b \ge 0] + \eta^t_{-}Dist_b + \eta^t_{+}Dist_b \cdot \mathbf{1}[Dist_b \ge 0] + \varepsilon_{bt}$$

with standard errors clustered at the county level. The sample is limited to blocks around straight segments of lot size borders, detected through the procedure in Section 3. In addition, the sample only includes minimum lot sizes of up to 6,000 square feet, and where observed density of single-family homes shifts more than 2,000 square feet outside of the lot size border. Section 4.2 gives the exact definitions of the samples. Household density is calculated using the area of underlying block boundaries, in square kilometers.

Sources: Calculations from 2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.



Figure 4: Dynamic racial disparities for lot size boundaries in high-density development

*Notes:* This figure presents border discontinuity effects for the block-level racial minority share  $Share^m$ , using data from 1980 to 2020. Effects are estimated over the high-density sample defined in Section 4.2. The sample is limited to blocks around straight segments of lot size borders, detected through the procedure in Section 3. In addition, the sample only includes minimum lot sizes of up to 6,000 square feet, and where observed density of single-family homes shifts more than 2,000 square feet outside of the lot size border. Effects are estimated from the fixed effects model

$$Share_{bt}^{m} = \alpha_{j(b)t} + \beta^{t} \mathbf{1}[Dist_{b} \ge 0] + \eta_{-}^{t} Dist_{b} + \eta_{+}^{t} Dist_{b} \cdot \mathbf{1}[Dist_{b} \ge 0] + \varepsilon_{bt},$$

with standard errors clustered at the county level. *Sources:* Calculations from 1980–2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.



Figure 5: Racial disparities around minimum lot sizes, broken down by housing vintage

(a) Nonwhite share as outcome

(b) Black American share as outcome

*Notes:* This figure presents border discontinuity effects on the 2020 Census block-level Black share, estimated across stratified samples of lot size segments. Effects are estimated from the fixed effects model described in Section 5.3, with standard errors clustered at the county level. The samples reflect distinct urban contexts around straight segments of lot size borders, detected through the procedure in Section 3. In addition, the samples are split by the median year built of properties in the area around the segments: the *contemporary sample* includes only areas all built after 1980. Section 4.2 gives the exact definitions of the samples.

Sources: Calculations from 1990–2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.

Parameter name	Symbol	Value
Hexagonal tile radius, arcseconds	R	18
Count of lots at bunched sizes	$\underline{N}$	10
Bunching range factor	M	1.25
Misclass. rate threshold	$\overline{m}_{err}$	0.35
Linear SVM penalty	С	1.00
Neighboring lots for KNN extension	k <sub>mult</sub>	8
Radius for KNN extension	r <sub>mult</sub>	1.20

Table 1: Value of Parameters in Automated Border Detection Method

*Notes:* This Table lists the key parameters used in different stages of the automated detection procedure for lot size discontinuities, as detailed in Section 3. Except for dimensionless parameters, parameter units are given in the leftmost column.

Statistic		Range of MLS in subsample					
		Total	1–6000	6000–11000	11000-22000	22000+	
MLS level (sq. ft.)	Mean St. Dev.	12,316.3 15,135.9	5,220.2 798.0	8,154.4 1,482.1	15,284.7 3,855.4	46,333.9 34,140.0	
	Ν	128,061	33,029	55,246	28,636	11,150	
Median year built	Mean St. Dev. N	1965 21 110,773	1958 25 26,572	1964 21 48,115	1968 18 26,113	1978 16 9,973	
Distance from CBD (km)	Mean St. Dev. N	26.5 18.9 128,061	23.4 17.5 33,029	26.1 19.0 55,246	27.6 18.4 28,636	34.5 21.2 11,150	
Population of treated area, 2010	Mean St. Dev. N	374.5 617.1 24,040	824.3 1,086.0 3,188	480.7 609.4 8,168	214.6 273.3 7,416	92.7 145.5 5,281	

Table 2: Summary Statistics for Minimum Lot Size Treated Areas

*Notes:* This summary table plots statistics on the predetermined character of residential development, for blocks determined to be in a minimum lot size district following the detection procedure in Section 3. The level of observation is Census block based on 2010 boundaries. Both the full sample is summarized, along with four subsamples based on the level of lot size regulation applied in treated areas. MLS level and year built variables are defined at the level of interior cell, then matched to blocks contained in those cells. The final variable is observed at the level of treatment area, which is the union of all blocks identified to be surrounding a regulatory boundary segment and where development is restricted by the lot size regulation.

Sources: Calculations from 1980-2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.

Statistic		High density sample Treated Comparison		Large density shift sample Treated Comparison		
Median	Mean	1,963	1,957	1,966	1,961	
year Dunt	N	24 7,999	10,807	10,632	19,758	
Distance	Mean	25.0	19.1	25.6	22.0	
from CBD	St. Dev.	18.1	17.6	19.6	19.2	
(km)	Ν	10,058	14,924	12,591	26,836	
Population	Mean	763.2	1,100.3	463.7	876.4	
of area, 2010	St. Dev.	988.2	2,332.7	629.3	1,310.6	
	Ν	1,069	1,204	2,023	2,496	
% Black in	Mean	16.7	29.1	10.5	18.0	
block, 1980	St. Dev.	32.2	39.7	25.4	33.2	
	Ν	3,168	7,542	4,146	13,088	
% minority	Mean	25.6	38.9	17.2	25.6	
in block,	St. Dev.	32.8	39.6	28.0	34.4	
1980	Ν	3,168	7,542	4,146	13,088	
% rental	Mean	31.1	48.5	24.5	40.4	
units, 1980	St. Dev.	30.2	32.1	28.9	30.0	
	Ν	2,959	6,928	3,887	12,114	
Treated MLS		0	-6000	6000-11000		
Din with Compared		200	0000	4000-11000		

*Notes:* This summary table plots statistics on the predetermined character of residential development for two types of blocks. Blocks determined to be in a minimum lot size district following the detection procedure in Section 3 is in the "Treated group." Blocks in adjacent areas developed at a specified elevated density compared to the treated areas is in the "Comparison group." Results are plotted for two urban context-specific samples, each representing a subset of all blocks in the analysis sample. The definitions of those context-specific samples are given in Section 4.2. The level of observation is Census block based on 2010 boundaries. The population variable is observed at the level of treatment area, which is the union of all blocks identified to be surrounding a regulatory boundary segment and where development is restricted by the lot size regulation.

Sources: Calculations from 1980–2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.

	Block level shares			Block level shares		
BD Estimates	Rented Units	> 62 y.o.	$\leq$ 18 y.o.	Rented Units	> 62 y.o.	$\leq$ 18 y.o.
2020 Data	-0.015	0.010	0.005	0.039	-0.003	0.014
	(0.030)	(0.014)	(0.011)	(0.026)	(0.020)	(0.010)
2010 Data	-0.034	-0.001	-0.001	-0.025	0.031**	-0.009
	(0.022)	(0.014)	(0.009)	(0.019)	(0.013)	(0.009)
1980 Data	-0.031	-0.024	0.0003	-0.026	0.007	—0.005
	(0.042)	(0.022)	(0.016)	(0.034)	(0.017)	(0.011)
Jurisdiction FE	X X X X		X X X X			
Treated MLS	0–6000		6000–11000			
Diff With Compared	2000–6000		4000–11000			
Total <i>N</i>	58667		91105			

Table 4: Covariate Balance Over Time around MLS Discontinuities

*Significance levels:* \* = 10%; \*\* = 5%; \*\*\* = 1%.

*Notes:* This table presents outputs of border discontinuity designs over Census blocks *b* in year *t* for racial minority *m*,

$$Z_{bt} = \alpha_{i(b)t} + \beta^t \mathbf{1}[Dist_b \ge 0] + \eta^t_{-}Dist_b + \eta^t_{+}Dist_b \cdot \mathbf{1}[Dist_b \ge 0] + \varepsilon_{bt},$$

where Z describes a confounding variable at the block level. Each column plots a separate confounder available in the Census tabulations. Separate estimates are made for different years of Census data, and for two samples representing different urban contexts that are detailed further in Section 4.2. In the table, the key density ranges defining the context-specific sample are listed. Point estimates and standard errors are based off of the robust nonparametric procedure in Calonico, Cattaneo and Titiunik (2014). Across specifications, fixed effects are set at the jurisdiction-year level. Standard errors are calculated clustering at the county-year level.

Sources: Calculations from 1980–2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.

	Block Nonv	vhite Shares	Block Black Shares		
BD Estimates	(1)	(2)	(1)	(2)	
2020 Data	0.001 (0.003)	-0.006*** (0.002)	-0.007*** (0.002)	-0.008*** (0.001)	
2010 Data	-0.012*** (0.003)	-0.017*** (0.002)	-0.009*** (0.002)	-0.010*** (0.001)	
1980 Data	-0.006 (0.004)	-0.009*** (0.003)	-0.008** (0.004)	-0.009*** (0.003)	
Jurisdiction FE Border FE	Х	Х	Х	Х	
Total N	1113777		1113777		

Table 5: Effects of Lot Size Borders for Pooled Sample

Significance levels: \* = 10%; \*\* = 5%; \*\*\* = 1%.

*Notes:* This table presents outputs of border discontinuity designs over Census blocks b in year t for racial minority m,

Share<sup>*m*</sup><sub>*bt*</sub> = 
$$\alpha_{j(b)t} + \beta^t \mathbf{1}[Dist_b \ge 0] + \eta^t_-Dist_b + \eta^t_+Dist_b \cdot \mathbf{1}[Dist_b \ge 0] + \varepsilon_{bt}$$
,

where shares are taken over all residents who are not non-Hispanic white, as well as just for Black Americans. For each outcome, two models are estimated with different fixed effects specifications. All data surrounding the regulatory segments detected using the procedure in Section 3 are used. The border discontinuity specification is parametric, as we do not drop observations and fit linear functions on both sides of the border discontinuity. Standard errors are calculated clustering at the county-year level.

Sources: Calculations from 1980–2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.

	Block level shares			Block level shares		
BD Estimates	Nonwhite	Black	Asian	Nonwhite	Black	Asian
2020 Data	-0.028*	-0.034**	-0.008	-0.033	-0.021	-0.004
	(0.015)	(0.014)	(0.010)	(0.024)	(0.019)	(0.006)
2010 Data	-0.067***	-0.050***	0.002	-0.042***	-0.040***	—0.006
	(0.019)	(0.016)	(0.010)	(0.014)	(0.014)	(0.009)
1980 Data	-0.032	0.003	-0.005	-0.030	-0.048**	0.001
	(0.032)	(0.029)	(0.005)	(0.034)	(0.022)	(0.005)
Jurisdiction FE Treated MLS Diff With Compared Total <i>N</i>	X	X 0–6000 2000–6000 59634	Х	X 6 4	X 0000–11000 000–11000 92672	Х

Table 6: Dynamic Effects of MLS Discontinuities on Race, Other Demographics

*Significance levels:* \* = 10%; \*\* = 5%; \*\*\* = 1%.

*Notes:* This table presents outputs of border discontinuity designs over Census blocks b in year t for racial minority m,

$$Share_{bt}^{m} = \alpha_{j(b)t} + \beta^{t} \mathbf{1}[Dist_{b} \ge 0] + \eta_{-}^{t} Dist_{b} + \eta_{+}^{t} Dist_{b} \cdot \mathbf{1}[Dist_{b} \ge 0] + \varepsilon_{bt},$$

where each column plots shares for a different group *m*, "Nonwhite" referring to all residents who are not non-Hispanic white. Separate estimates are made for different years of Census data, and for two samples representing different urban contexts that are detailed further in Section 4.2. In the table, the key density ranges defining the context-specific sample are listed. Point estimates and standard errors are based off of the robust nonparametric procedure in Calonico, Cattaneo and Titiunik (2014). Across specifications, fixed effects are set at the jurisdictionyear level. Standard errors are calculated clustering at the county-year level. *Sources:* Calculations from 1980– 2020 NHGIS Tables (Manson et al. (2021)) and CoreLogic Tax Records.