

Online Appendix

Dividing Lines: Racial Segregation across Local Government Boundaries

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A Data

We combine Geographic Information Systems (GIS) data on local government boundaries with geographic data from four waves of the decennial census to understand segregation in the context of jurisdictional divisions. GIS data on local boundaries is obtained via the US Census Bureau's TIGER/Line data for definitions of school districts (local education agencies), cities (incorporated Census places), and counties for the decennial years 1990, 2000, 2010 and 2020. We also use a dataset on school attendance boundaries from data services firm Precisely for the school year 2019-20.¹

Our primary definition of a neighborhood is a Census block, small geographic areas that coincide with city blocks in densely populated urban settings. Typically, researchers use census tracts as the primary unit for the analysis of segregation. However, we are interested in measuring segregation within sometimes very small units, such as small cities or school attendance boundaries, which may be composed of only one or two Census tracts. Unlike blocks, tracts may be masking important variation in neighborhood composition within these small units.²

We collect census block level data for the decennial censuses between 1990-2020 via the National Historical Geographic Information System (NHGIS). Our analysis focuses on population counts by race and ethnicity. We study the four largest groups by population: White, Hispanic, Black and Asian. Our segregation measures focus on the separation of the White population from the Hispanic, Black, and Asian population (see below for a measurement discussion).

Finally, we bring in data on public school inputs and outcomes, to assess the relevance of boundary divisions for existing inequality in public good provision. We collect the 2011-2017 waves of the Department of Education's Civil Rights Data Collection (CRDC), obtaining school level measures of teacher and other staff characteristics, student discipline rates, and access to advanced tracking

¹ We are forced to rely on privately supplied data on attendance boundaries, as the federal government does not have a regular collection of these policies.

² Importantly, our measures of between-jurisdiction segregation is invariant to how we define neighborhoods.

programs. We make use of the Stanford Education Data Archive (SEDA) school level dataset on average student scores on state standardized exams over the period 2008-2017. We also exploit Georgetown University's National Education Resource Database on Schools (NERDS) school level dataset for the 2018-19 school year on total expenditures.

B The History of Local Government Boundaries

The US system of local governments is vast, made up of thousands of fiscally independent entities, almost all of which have the power to levy property taxes. Below the federal government and the fifty state governments, most public sector activity can be organized in three groups: two generalpurpose governments – county governments and municipal governments – and school districts.³One noteworthy feature of US local governments (in contrast to other countries) is the separation of school districts from municipal and county governments which control services like sanitation, housing, police and fire departments. The overlay of municipal and school boundaries creates a rich patchwork of invisible lines that have important implications for public good provision.

Boundary lines are not limited to the already numerous jurisdictional lines that divide local governments. Most municipal and school district governments draw their own administrative maps, ranging from school attendance boundaries, land use zoning codes, to police and fire districts. An overlay of every administrative and jurisdictional line in any metropolitan area shows a seemingly chaotic criss-cross of lines. It is important to understand the history, intention, and ultimate impact of these urban divisions on racial segregation and racial inequality in public good provision. For example, Shertzer et al. (2016) find that predominantly minority neighborhoods in Chicago were more likely to be zoned for noxious activities as part of industrial land use.

Local governments differ dramatically in the amount of property taxes they collect, and since much of their funding is localized, service quality differs dramatically. A vast literature documents these differences in service quality across local governments and studies their causes. We provide some examples to highlight that local governments play an important role in a household's economic success and residential choice. In a classic study, Card and Krueger (1992) show that there is considerable variation in the return to education across states, and that it is substantially higher in states with better school inputs, such as lower pupil-teacher ratio and higher relative teacher pay. Epple and Sieg (1999) estimate an equilibrium model of household preferences and local public

³ The Census Bureau also recognizes township governments and other special districts (such as independent transportation districts like Bay Area Rapid Transit (BART) in the San Francisco Bay Area) as independent bodies in the local public sector, but obtaining data on activities and boundaries for these bodies is difficult, and hence they lie outside of the scope of this study.

goods, finding that households value lower crime and higher education expenditures. Boustan (2013) compares house prices on either side of city-suburb boundaries over time and estimates that households are willing to pay substantial premia to live in high-income suburbs, particularly for better school quality and lower property taxes. Schönholzer (2021) pursues a similar approach to summarize household willingness to pay for all excludable public goods provided by municipalities and school districts, finding that around 11% of housing costs are due to variation in local public goods.

Given the important role local governments play in households' residential choices, we now turn to a brief summary of the boundaries that delineate the territorial extent of local governments and the nature of change of these boundaries over time. We distinguish between public education boundaries, which include school district boundaries and school attendance boundaries, and municipal service boundaries, which include city and county boundaries. The location of local government boundaries is determined both through the creation and elimination of local governments as well as changes to boundaries of existing local governments. The rules that govern boundary changes are set by state constitutions and may hence differ substantially from one state to the next.

B.1 Public Education Boundaries

Historically, US public education has been characterized by local control by independent school districts. During the early 20th century, there were practical reasons for decentralized public education provision and funding in low-density localities, derived as well from a long tradition of community control and local taxation (Goldin and Katz, 2003). Public schools were operated by nearly 117,000 independent districts during this time. Then, starting in the 1940s an era of district consolidation began that witnessed a 92% decline in the number of districts in the country. By 1980 there were only about 15,000 districts nationally, and today the number is closer to 13,000.

District mergers. The literature documenting the observable predictors of district mergers highlights the role of income and racial heterogeneity (Nelson, 1990; Kenny and Schmidt, 1994; Brasington, 1999). Gordon and Knight (2008, 2009) consider the problem facing districts with potentially many possible neighbors to merge with, and how to properly estimate the role of characteristics in driving mergers. They find that socioeconomic characteristics are an important driver of merge likelihoods. Thus, it is likely realized merge patterns are linked to the increasing between district inequality witnessed in the last decades, as descriptive evidence has suggested

(Weiher, 1991; Richards and Stroub, 2014). More research is needed to understand the extent to which district mergers may have systematically exacerbated US inequality in public good provision.

School attendance boundaries. As the number of districts has fallen, intra-district attendance boundary policies have become increasingly important in determining sorting patterns. School quality varies considerably within districts, and variation in average school test scores is correlated with residential sorting and real estate prices Black (1999); Bayer et al. (2007). There is observational evidence that some districts set attendance boundaries in ways meant to influence school integration, although most adhere to boundaries closely following neighborhood demarcation Monarrez (2021). Desegregated attendance boundaries are more prevalent in districts under a desegregation order, in those with relatively lower racial animus, and in those facing lower commuting costs, suggesting that districts' boundary choice is a product of various trade-offs. Our ongoing work attempts to describe the rate at which school attendance boundaries change and the impact that school redistricting may have on housing markets.

District secessions. While the long-run trend in the number of school districts has flattened out, school district secessions have become increasingly common in recent years, hinting at a partial reversal from the previous trend of consolidation. Recent work has shown that district secessions in Memphis, Tennessee, led to sizable impacts on the housing market (Collins and Kaplan, 2017). However, to our knowledge, there is no systematic evidence on the impact of this recent wave of secessions on patterns of racial inequality nationwide. In ongoing work with co-authors, we are undertaking a systematic analysis of the impact of recent district secession events on student achievement outcomes and inequality.

B.2 Municipal Service Boundaries

Municipalities and counties provide a wide range of services to residents, including public safety, emergency response services, utilities, transportation infrastructure, courts, and jails. County governments are in charge of some of these services throughout the US, except in Connecticut, Rhode Island, and the District of Columbia, where counties serve simply as statistical units for census enumeration. Municipal and county governments are also responsible for zoning and land use regulation, policy tools that restrict the use and development of economic activity and housing. Unlike counties and school districts, many parts of the US lie outside *any* incorporated city.

These unincorporated areas include many impoverished and high-minority urban neighborhoods (Anderson, 2008) that receive only limited urban services from their county. For example, in Los Angeles County alone, more than one million households live in such areas and are effectively excluded from urban services provided by nearby cities. But unincorporated areas are also commonly found in rural areas with little need or desire for urban services.

Incorporations. As unincorporated areas experience more development, they may choose to incorporate as a city so as to provide additional public goods and gain local control. There is a long tradition of municipal incorporation in the US, with more than ten thousand incorporations before 1900, many of them having no more than a few hundred residents. Over the course of the 20th century, the trend in the number of municipal governments has been moving in the opposite direction of that of school districts: it nearly doubled from 10,602 in 1900 to just above 19,000 in 1982. Since then, growth has leveled off, arriving at 19,495 in 2017. Incorporations are driven by a variety of local interests (Rice et al., 2014). Besides the provision of public services, residents may seek to control land use and growth. In the postwar boom of suburban cities, race and class divisions played a central role in incorporation (Burns, 1994). Communities may also incorporate to fight off other cities from encroaching on their territory.

Annexations. Incorporations are not the only way that unincorporated areas may become subject to municipal governance. Another common alternative are municipal annexations – territorial expansions of existing city governments into unincorporated areas. While it is true that boundary changes between existing cities are rare (Epple and Romer, 1989), annexations of unincorporated territory are extremely common: in the last twenty years, more than 100,000 annexations occurred (U.S. Census Bureau Government Division, 2013). Most of these are “greenfield” annexations, providing city services to uninhabited territory for future housing development, but some of them affect built-up neighborhoods that were historically excluded from incorporation.

In the past, central cities sometimes absorbed entire neighboring cities, such as when New York City annexed the independent city of Brooklyn in 1898, which was the fourth-largest city in the US at the time. But over the course of the early 20th century, most states introduced laws that prevented such takeovers of existing cities. Austin (1999) finds that the ability to offset the effects of suburbanization and white flight continued to motivate annexations in the postwar era. As a result, central cities that were able to absorb most of their suburbs tend to be on firmer fiscal ground than those that became locked in by a belt of affluent but independent suburban cities (Rusk, 1993).

County Boundaries Counties constitute the basic division of state territory into local units, and as such, their number grew dramatically as the United States expanded westwards. However, as the last states joined the Union, the number of counties largely stagnated. Correspondingly, the number of county governments has been almost unchanged since 1942, falling only slightly from 3,050 to 3,031. Boundaries of counties have also changed only rarely in the last fifty years (U.S. Census Bureau Government Division, 2013).

C Boundary Sorting Model

In this appendix, we show under what conditions the minority share of households is discontinuous at the boundary in the model outlined in Section 3.1. We assume that households value locations $\varphi > 0$ and public goods $\lambda_t > 0$, as well as that parameters and the distributions of incomes are such that in equilibrium, the following inequalities hold: $\ell_M^*(\bar{y}_M) > 0.5$ and $\ell_W^*(\bar{y}_W) < 0.5$ for

$$\bar{y}_t = \frac{(1 + \pi_t) [\Lambda_t p(0.5) - \lim_{\ell \rightarrow 0.5} p(\ell)]}{\Lambda_t - 1}$$

and $\Lambda_t = e^{\varphi \lambda_t \Delta x}$. This assumption essentially restricts how strongly location choices of different household types can diverge in equilibrium.

Proposition. (*Discontinuous minority share at the boundary*). Consider the model laid out in Section 3.1. Define $G_t(\ell) = \int 1[\ell_t^*(y) \leq \ell] dF_t(y)$ as the share of households of type t that locate at ℓ or below, and let $g_t(\cdot) = G_t'(\cdot)$ be the density of households of type t at \cdot . The density of minority households falls discontinuously at the boundary:

$$\lim_{\ell \rightarrow 0.5} g_M(\ell) > g_M(0.5)$$

if and only if at least one of two conditions holds:

1. Preferences for or access to the public good are lower for minorities: $\lambda_M < \lambda_W$;
2. Minorities experience price discrimination in the housing market: $\pi_M > 0$.

Proof. We proceed in three steps. First, we show that households sort along ℓ strictly according to their income. This allows us to focus on households at the boundary. Second, we show that the equilibrium price jumps at the boundary. Third, utility of minority households at the boundary is continuous in ℓ if and only if at least one of the conditions in the Proposition holds.

Step 1. $v_t(\cdot)$ is strictly increasing for each t . Suppose $\ell_2 > \ell_1$, which implies $v_t(\ell_2) > v_t(\ell_1)$ for both t . For markets to clear, it must be that $p(\ell_2) > p(\ell_1)$, otherwise no household would choose ℓ_1 . A household with income y of type t chooses ℓ_2 over ℓ_1 iff

$$v_t(\ell_2) - v_t(\ell_1) > \log(y - (1 + \pi_t)p(\ell_1)) - \log(y - (1 + \pi_t)p(\ell_2)).$$

The right-hand side is strictly decreasing in y . It follows that any richer household has the same preference. Hence, $\ell_t^*(y)$ is strictly increasing and continuous in y , sorting households within types by income.

Step 2. Given Step 1, there exists a strictly increasing and continuous inverse function $Y_t(\cdot)$. It maps a location choice to an income level for a household type with the property that $\lim_{\ell \rightarrow 0.5} Y_t(\ell) = Y_t(0.5) \equiv \hat{y}_t$ for both t . Let $u_t(y, \ell) = \log(y - p(\ell)) + \phi v_t(\ell)$. The equilibrium price at the boundary adjusts so as to make households at the boundary indifferent between either side. Specifically, it has to hold that

$$\lim_{\ell \rightarrow 0.5} \sum_t n_t u_t(\hat{y}_t, \ell) = \sum_t n_t u_t(\hat{y}_t, 0.5),$$

where $n_M = 2mF_M(\hat{y}_M)$ and $n_W = 2(1 - m)F_W(\hat{y}_W)$ are the shares of household types at the boundary. We can rewrite this as:

$$\sum_t n_t \log \left(\frac{\hat{y}_t - (1 + \pi_t) \lim_{\ell \rightarrow 0.5} p(\ell)}{\hat{y}_t - (1 + \pi_t) p(0.5)} \right) = \phi \Delta x \sum_t n_t \lambda_t \quad (2)$$

with $\Delta x = x_R - x_L$. Note that the right-hand side is strictly positive, and therefore the left-hand side has to be positive as well. But this can only be true if $\lim_{\ell \rightarrow 0.5} p(\ell) < p(0.5)$, that is, the price jumps discontinuously at the boundary.

Step 3. To examine the behavior of $g_M(\cdot)$ at the boundary, we look at how $u_M(\hat{y}_M, \ell)$ behaves at the boundary: if utility of minority households is continuous, then so is the density, and if utility drops discontinuously, then so does the density. For continuity, we require that $\lim_{\ell \rightarrow 0.5} u_M(\hat{y}_M, \ell) = u_M(\hat{y}_M, 0.5)$, which we can write as

$$\log \left(\frac{\hat{y}_M - (1 + \pi_t) \lim_{\ell \rightarrow 0.5} p(\ell)}{\hat{y}_M - (1 + \pi_t) p(0.5)} \right) = \phi \lambda_M \Delta x, \quad (3)$$

where the prices are such that (2) holds. If $\lambda_M = \lambda_W$ and $\pi_M = 0$, then the location choice depends only on income: $\ell_t^*(y) = \ell^*(y)$, and hence $\hat{y}_M = \hat{y}_W$. As a consequence of this and the assumptions on λ_t and

π_t , (2) and (3) are identical and must both hold, and thus $g_M(\cdot)$ (as well as $g_W(\cdot)$) is continuous at the boundary.

In contrast, if either $\lambda_M < \lambda_W$ or $\pi_M > 0$, then $\hat{y}_M(y) < \hat{y}_W(y)$ and hence $\hat{y}_M > \hat{y}_W$. Higher \hat{y}_M lowers the left-hand side of (3) compared to the left-hand side of (2), but due to the stated assumptions, by less than the drop on the right-hand side of (3) compared to the right-hand side of (2). Hence, the left-hand side of (3) is larger than its right-hand side, and hence $\lim_{\gamma \rightarrow 0.5} u_M(\hat{y}_M, \gamma) > u_M(\hat{y}_M, 0.5)$, or equivalently, $\lim_{\gamma \rightarrow 0.5} u_W(\hat{y}_W, \gamma) < u_W(\hat{y}_W, 0.5)$. \square

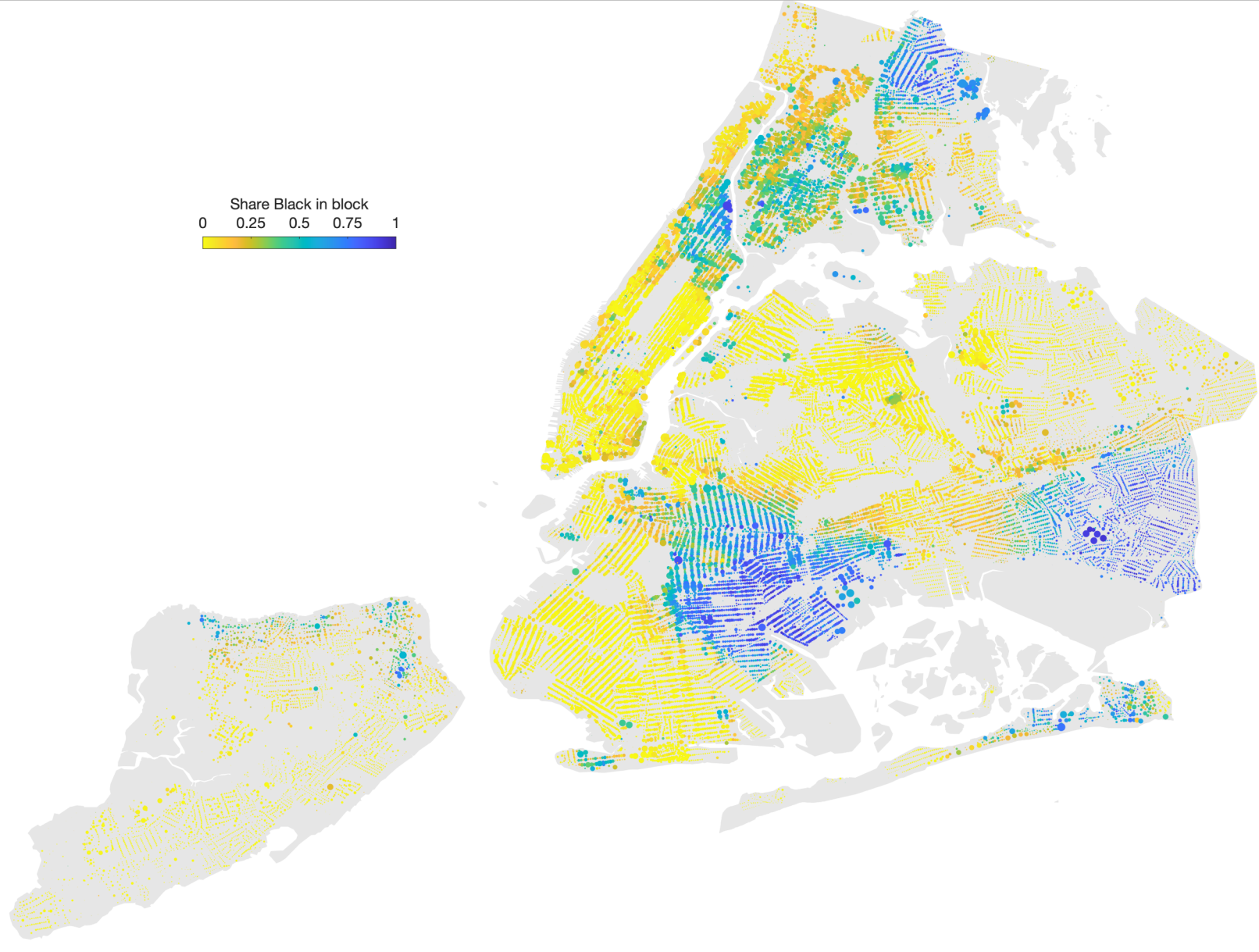
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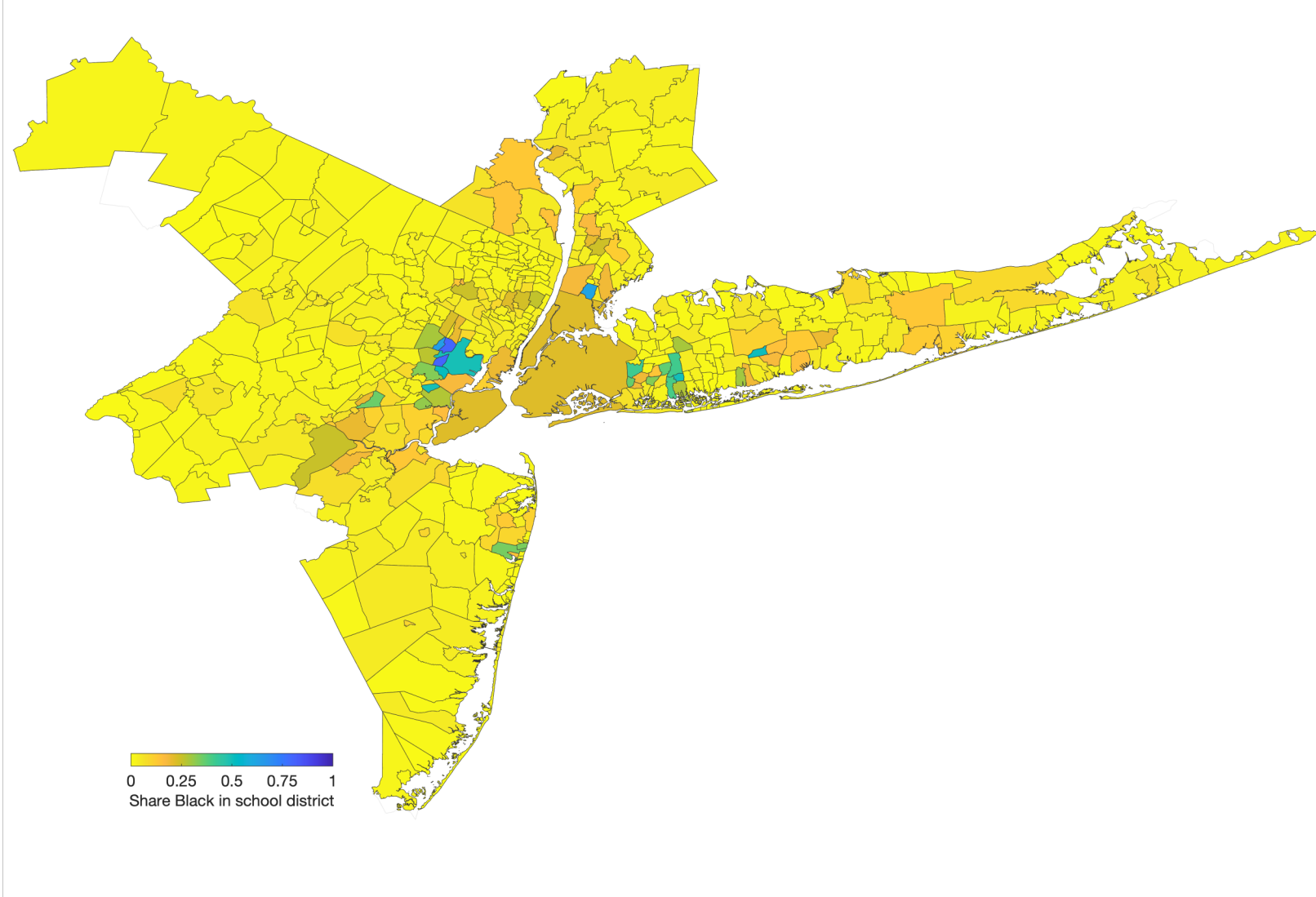
Appendix Figures

Figure A.1: Share Black residents in Census blocks, New York City, 2020



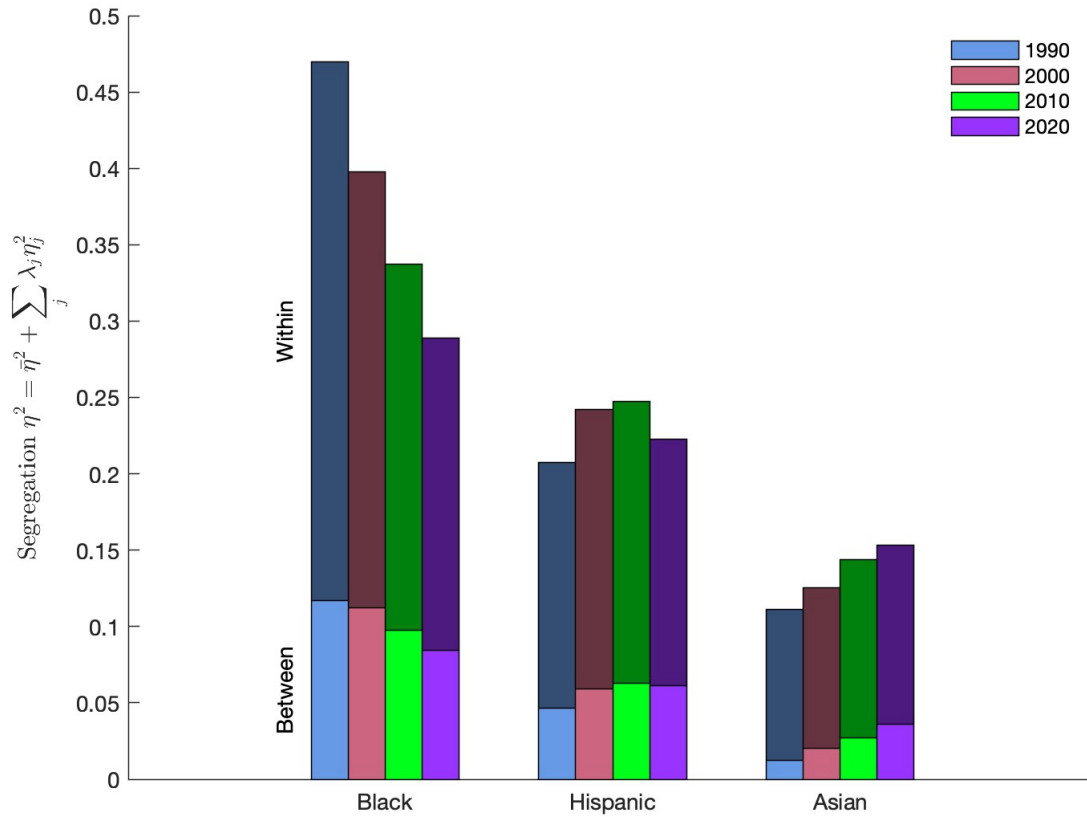
Notes: Map of the census blocks making up New York City. Population-weighted scatter dots correspond to the average latitude-longitude location of each block. Population demographic estimates based on 2020 census data. Heat map colors based on the Black share of block population.

Figure A.2: Share Black residents in school districts, New York metropolitan area, 2020



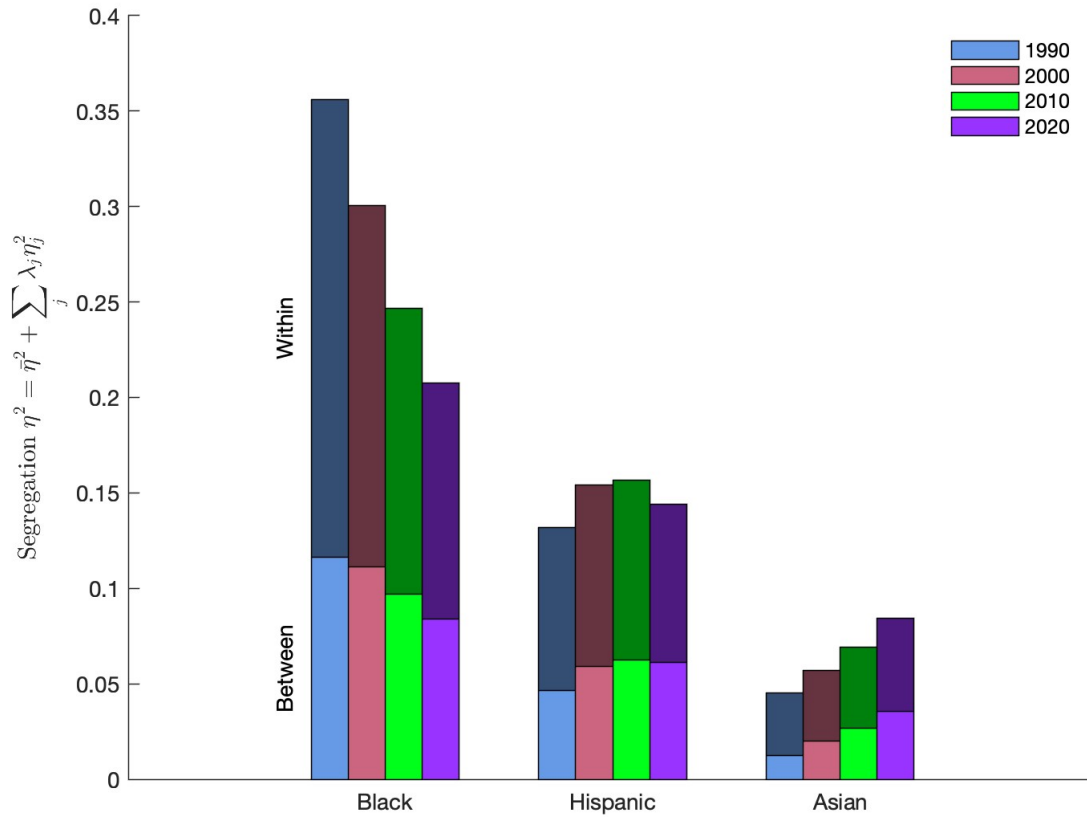
Notes: New York Metropolitan Statistical Area (MSA) and 502 independent school districts (local education agencies) according to 2020 census definitions. Population-weighted scatter plot shows the latitude/longitude location of census block centroids, with colors corresponding to the Black share of block residents. Figure shows a zoomed in section of western Long Island.

Figure A.3: Average metropolitan segregation of minorities, decomposed into between and within school districts, 1990-2020



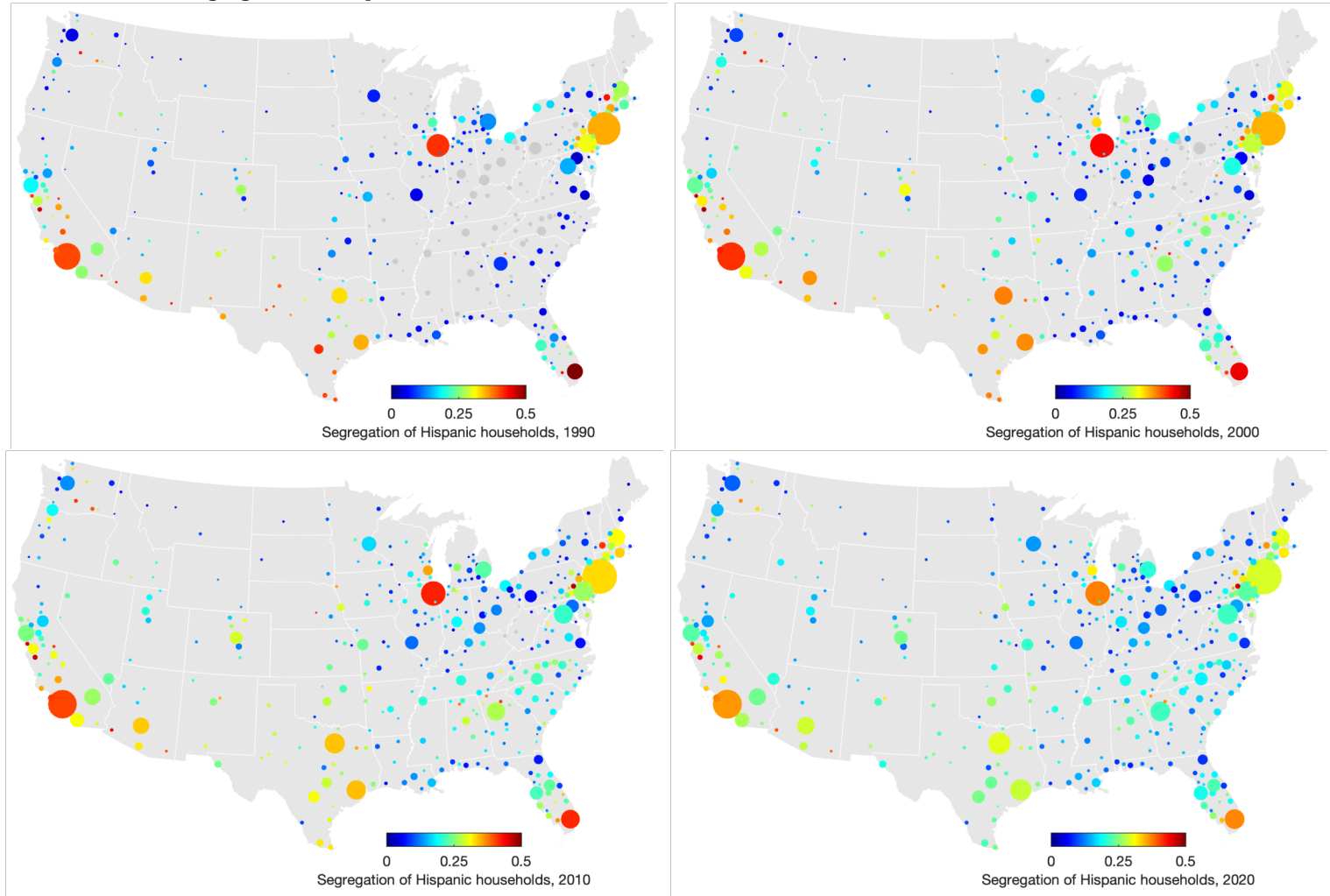
Notes: National average decomposition of total metropolitan segregation of Black, Hispanic, and Asian households. Lighter shade corresponds to between-school district segregation, darker shade to within-district segregation. Estimates based on the variance ratio index, using 1990, 2000, 2010, and 2020 census block data.

Figure A.4: Segregation of minorities, decomposed into between and within school districts, 1990-2020, tract-level measure of segregation



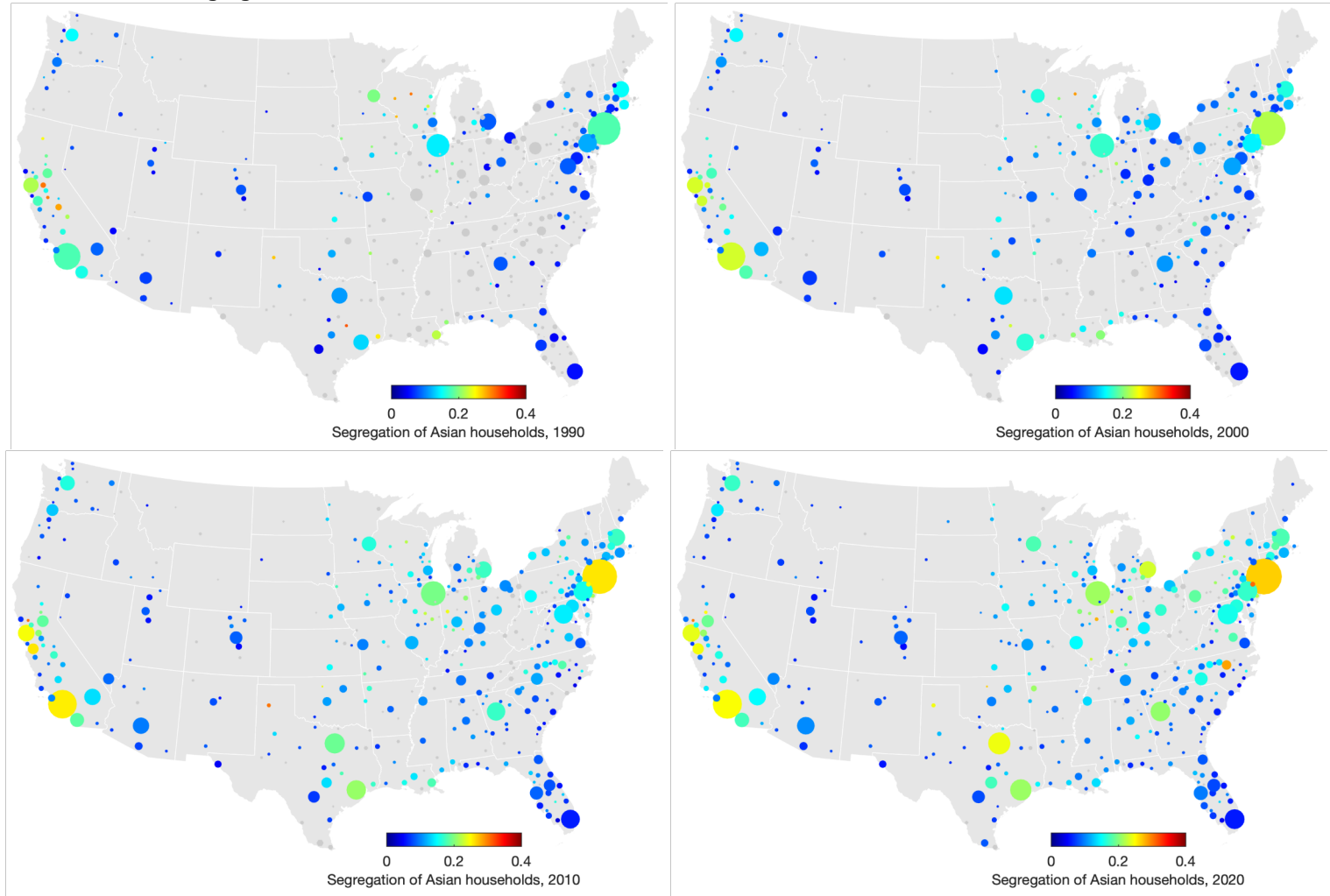
Notes: National average decomposition of total metropolitan segregation of Black, Hispanic, and Asian households. Lighter shade corresponds to between-school district segregation, darker shade to within-district segregation. Estimates based on the variance ratio index, using 1990, 2000, 2010, and 2020 census tract data.

Figure A.5: Metro-area segregation of Hispanic households, 1990-2020



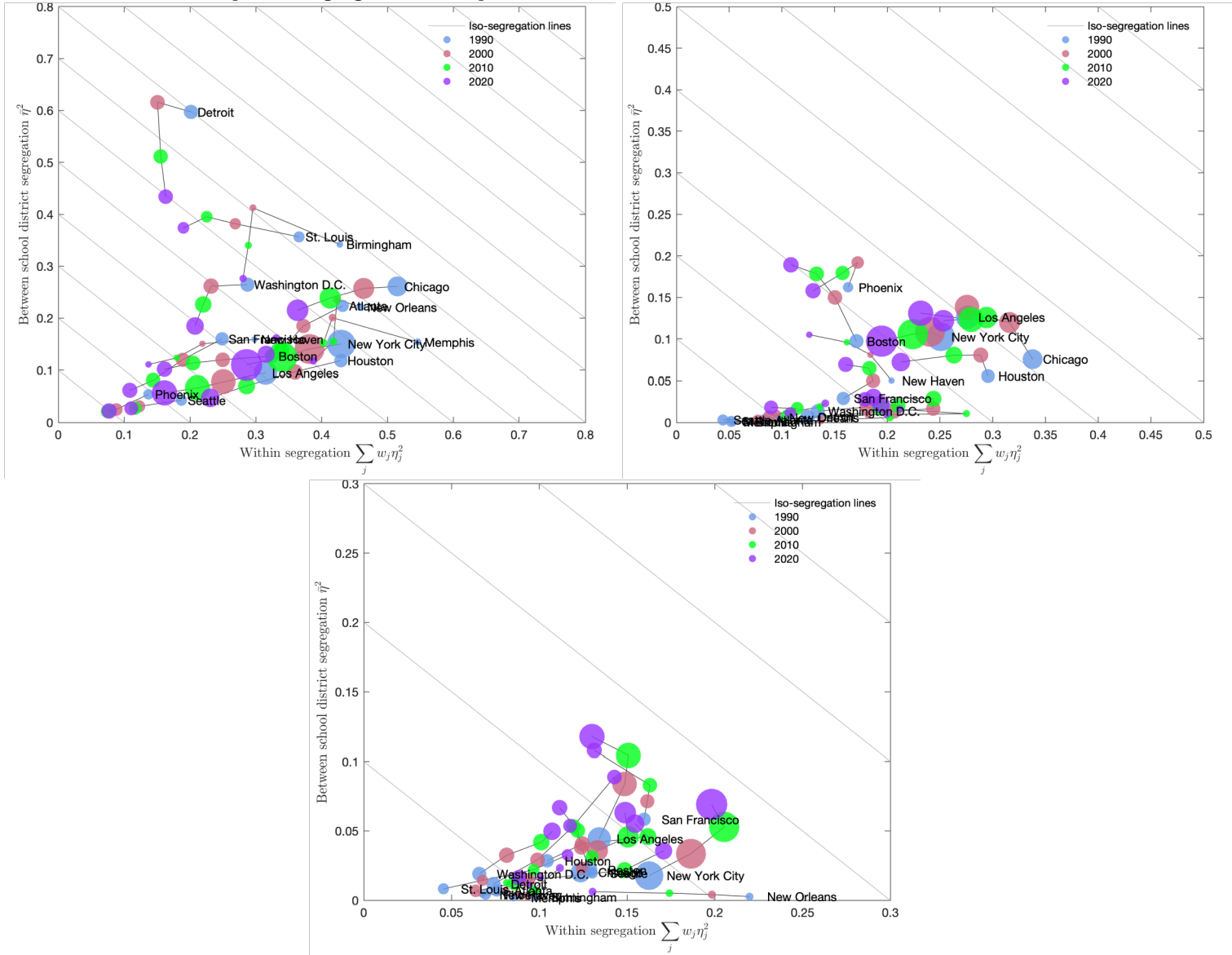
Notes: Location of US metropolitan areas, weighted by population. Heat coloring corresponds to total metropolitan segregation levels for Hispanic residents. Estimates based on the variance ratio index, using 1990, 2000, 2010, and 2020 census block data.

Figure A.6: Metro-area segregation of Asian households, 1990-2020



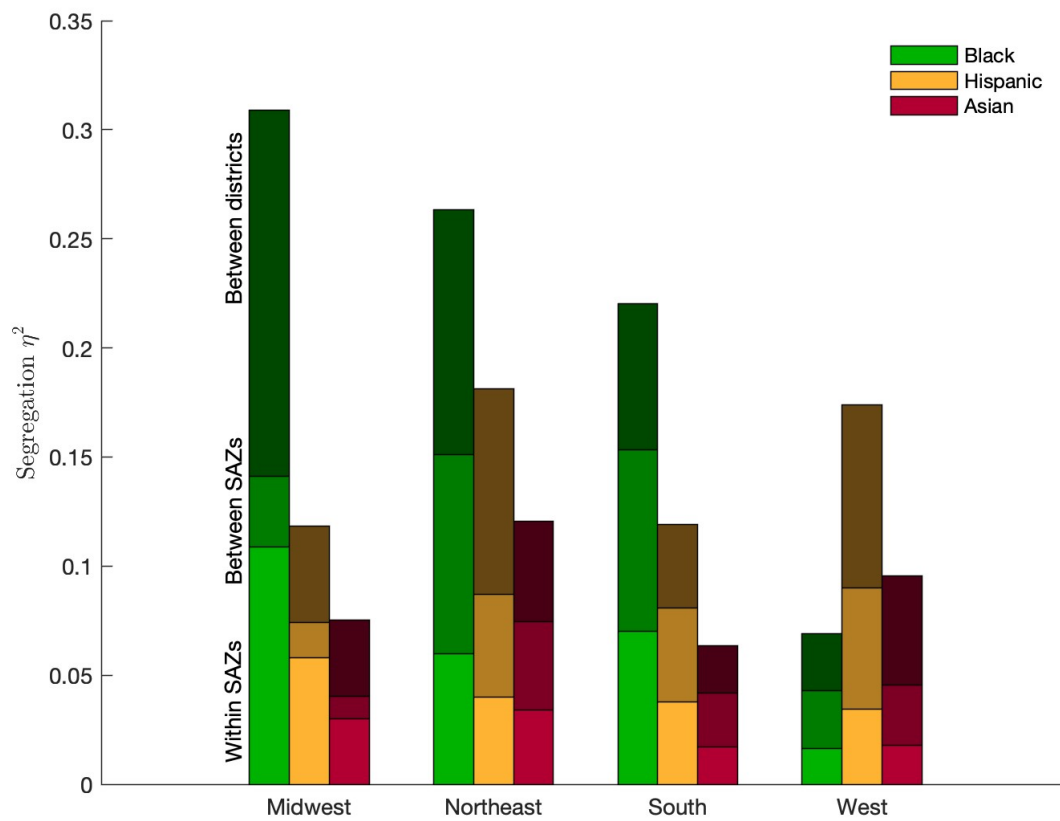
Notes: Location of US metropolitan areas, weighted by population. Heat coloring corresponds to total metropolitan segregation levels for Asian residents. Estimates based on the variance ratio index, using 1990, 2000, 2010, and 2020 census block data.

Figure A.7: Evolution of metropolitan segregation decomposition, selected areas, 1990-2020.



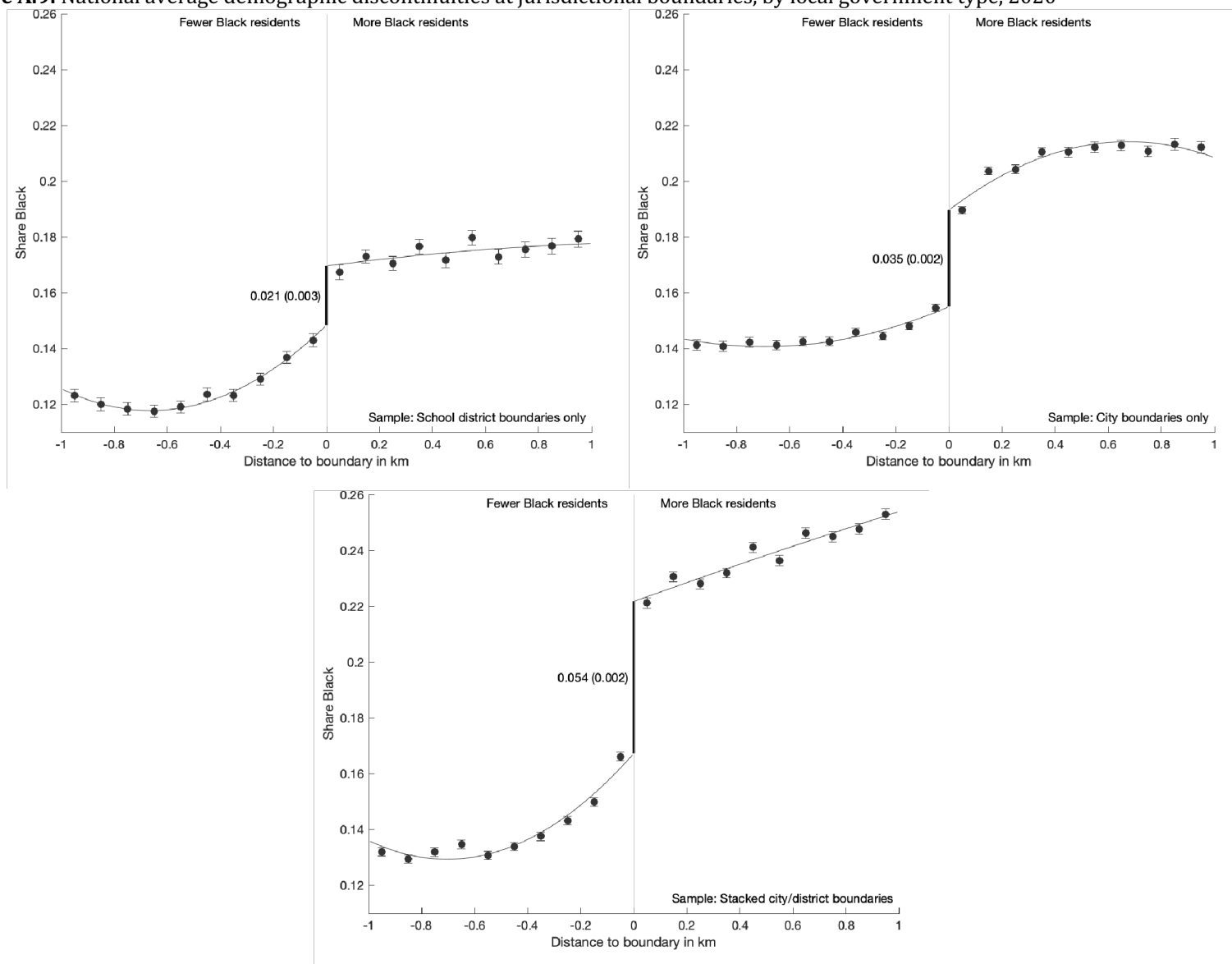
Notes: Population-weighted scatter plot of metropolitan areas, plotting between-district and within-district segregation. Plot colors denote decennial census years. Diagonal lines correspond to an "iso-segregation" locus of equal levels of total segregation.

Figure A.8: Segregation of minorities in 2020 by census region, decomposed into between school districts, between SAZs, and within SAZs, tract-level measure of segregation



Notes: SAZ = School Attendance Zones. Average metropolitan segregation by US Census region, based on 2020 census tract data. Decomposition terms shown in different color shades, according to the description in Section 4.5.1.

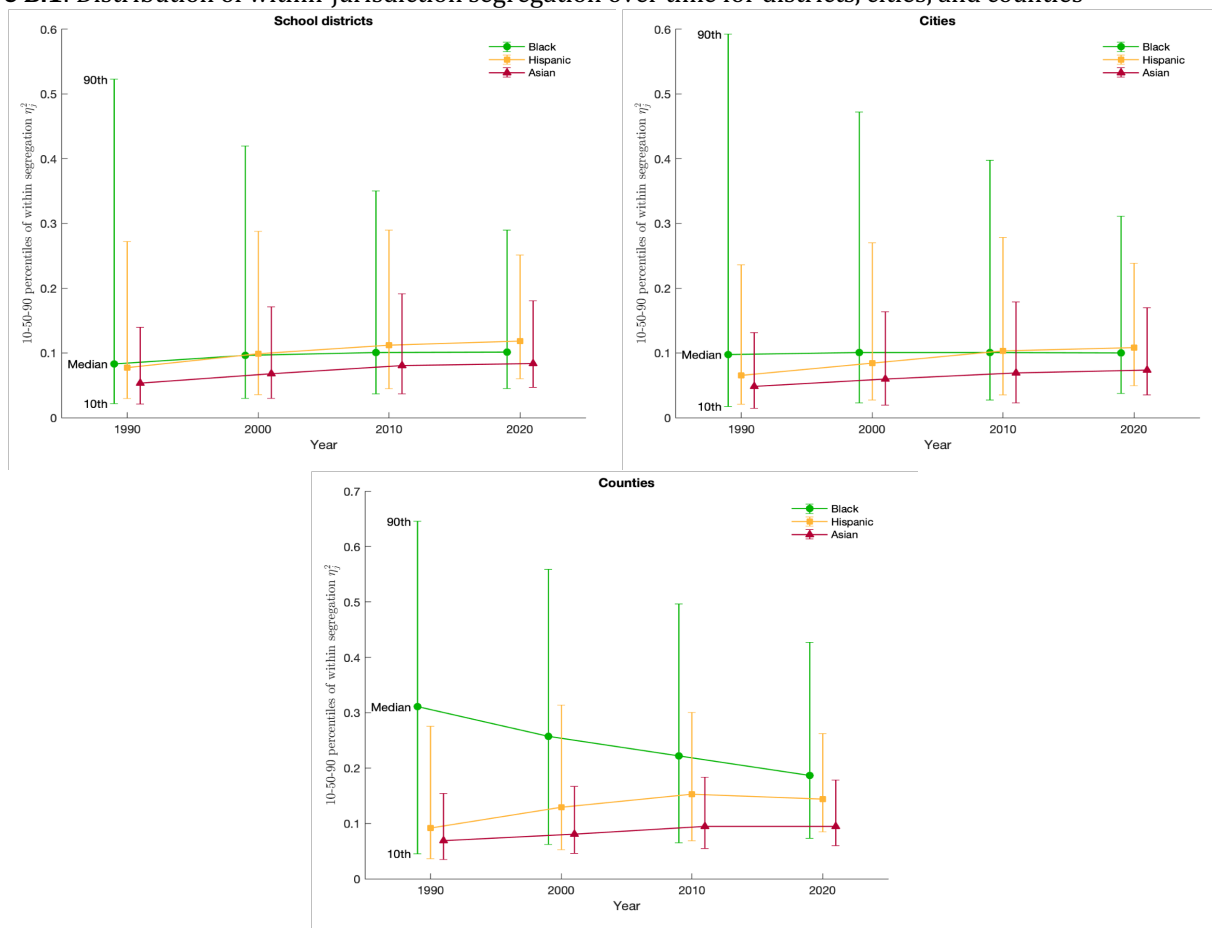
Figure A.9: National average demographic discontinuities at jurisdictional boundaries, by local government type, 2020



Notes: Spatial regression discontinuity (RD) plots of Black population shares against block distance to jurisdictional boundaries. Horizontal axis measures census blocks' perpendicular centroid distance to jurisdictional boundaries, where negative distance values correspond to the

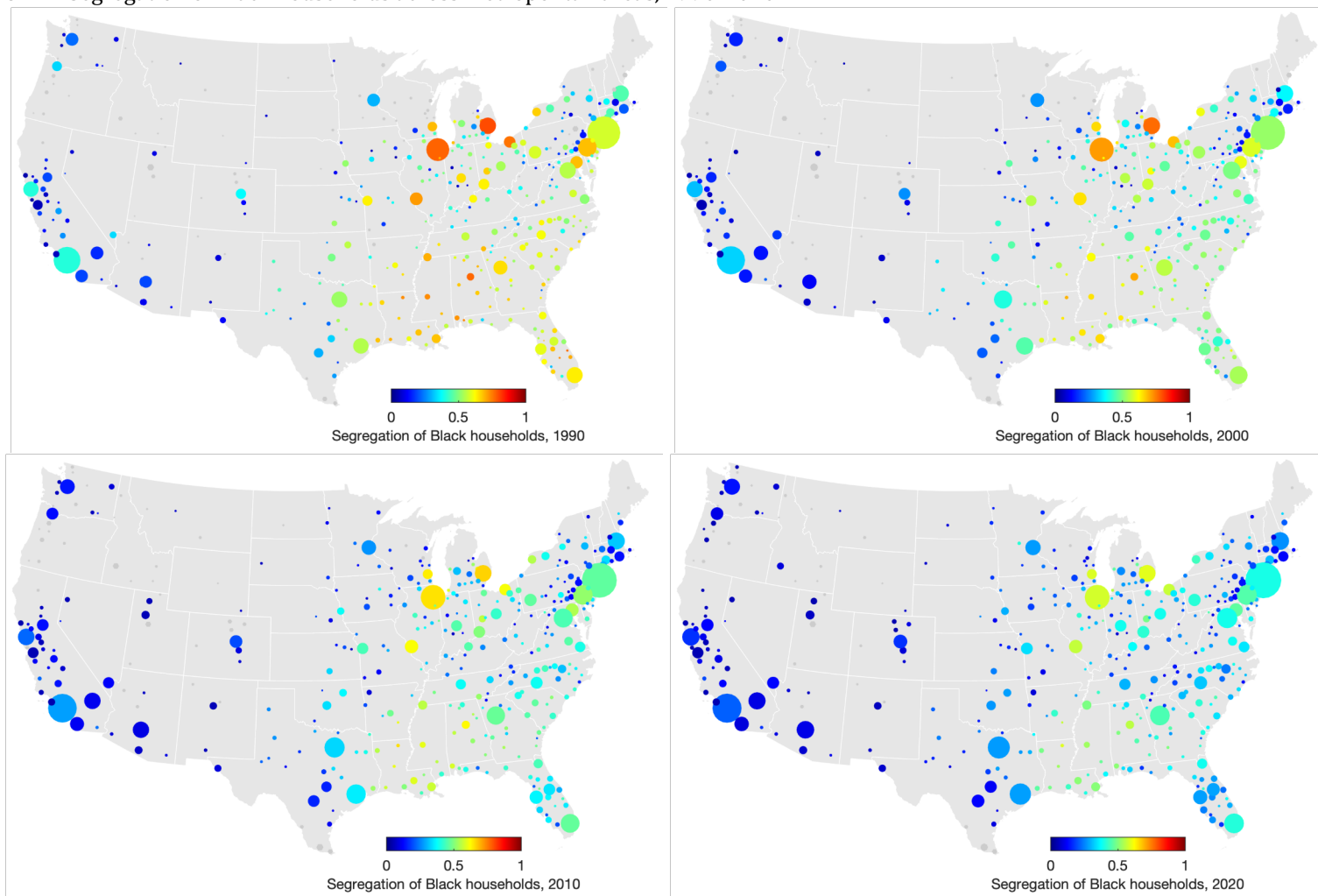
jurisdiction with fewer Black residents. Vertical axis shows the Black share of total census block population in 2020. Scatter plot shows binned means, with bins determined by equally-sized distance steps. Estimation sample is restricted to census blocks within 1 kilometer of a jurisdictional boundary and boundaries with at least one side with 5% Black residents or more, resulting in about 1.5M census blocks across 15,000 boundaries. RD coefficient (along with robust standard error) and quadratic spline fit reported.

Figure B.1: Distribution of within-jurisdiction segregation over time for districts, cities, and counties

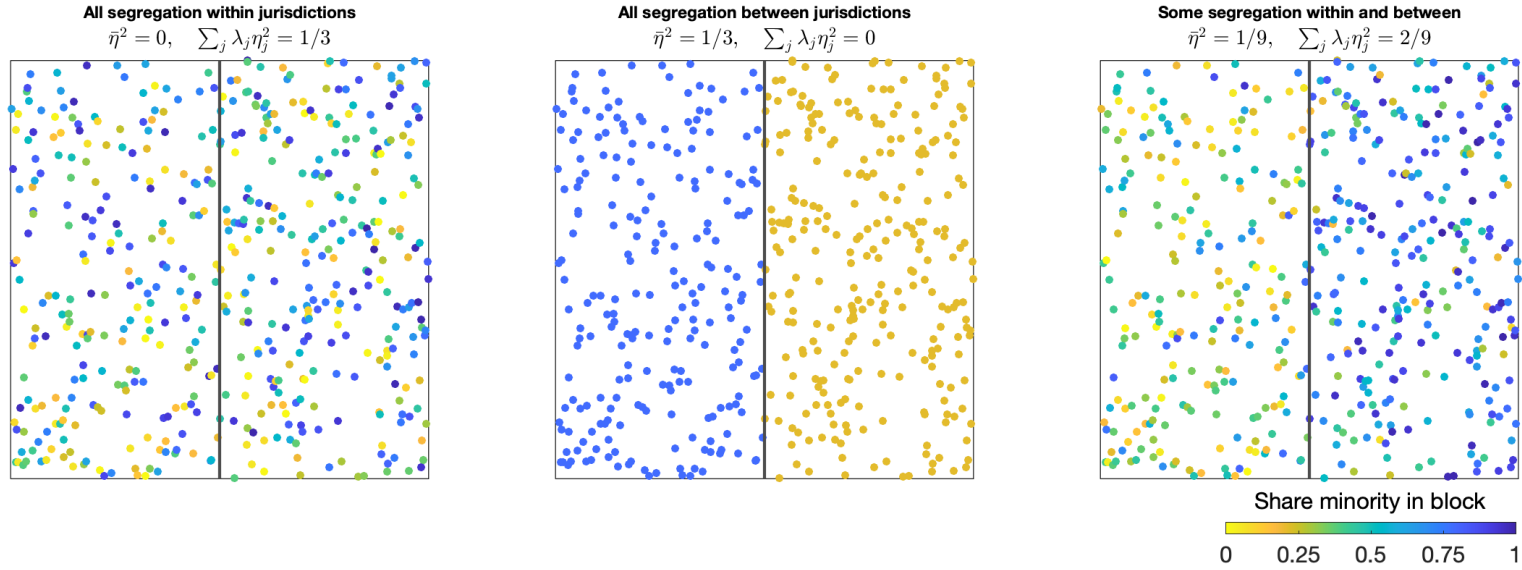


Notes: Summary of the national distribution of within-jurisdiction segregation of Black, Hispanic, and Asian residents, in cities, school districts and counties, showing the 10th, 50th, and 90th percentiles of each distribution. Estimates based on 1990, 2000, 2010, and 2020 census block data.

Figure B.2: Segregation of Black households across metropolitan areas, 1990-2020

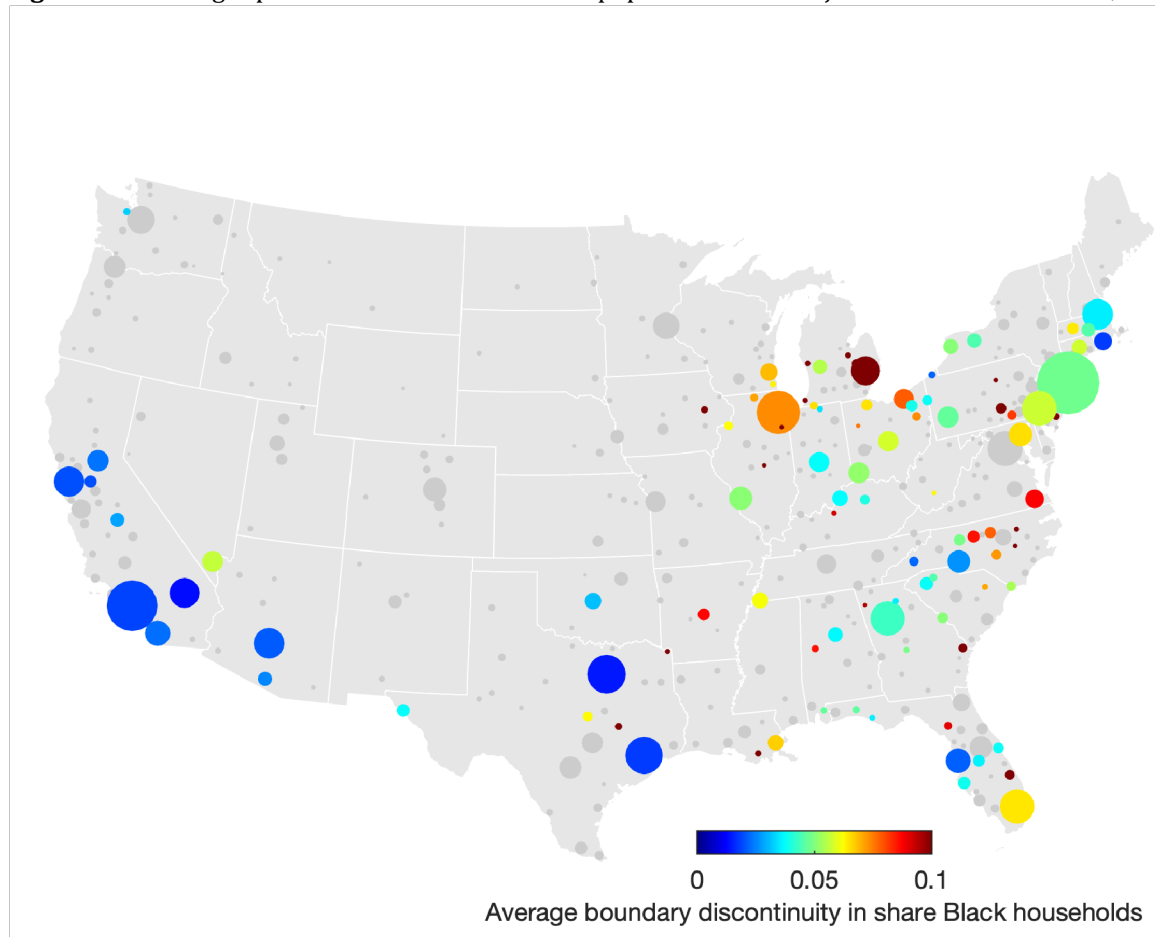


Notes: Location of US metropolitan areas, weighted by population. Heat coloring corresponds to total metropolitan segregation levels for Black residents. Estimates based on the variance ratio index, using 1990, 2000, 2010, and 2020 census block data.

Figure B.3: Illustration of within-segregation and between-segregation with simulated data

Notes: Each panel shows a simulated MA divided into two jurisdictions. Each MA has the same minority share $m = 0.5$ and the same level of total segregation $\eta^2 = 1/3$. The MA on the left was generated by drawing minority shares for blocks in both jurisdictions from Beta(1,1). For the MA in the middle, we set minority shares to $m_{i1} = (1 - 1/\sqrt{3})/2$ for all blocks in the left jurisdiction and $m_{i2} = (1 + 1/\sqrt{3})/2$ for all blocks in the right jurisdiction to ensure that $m = 0.5$ and an expectation of $\eta^2 = 1/3$ as desired. Finally, for the MA on the right, we draw $m_{i1} \sim \text{Beta}(1,2)$ and $m_{i2} \sim \text{Beta}(2,1)$, resulting in an expected $\eta^2 = 1/3$ and $\bar{\eta}^2 = 1/9$.

Figure B.4: Average spatial RD coefficient for Black population share at jurisdictional boundaries, across metropolitan areas, 2020



Notes: Map of US metropolitan areas weighted by total population. Colors denote the magnitude of a metropolitan area-specific RD coefficient of block population share Black as a function of block perpendicular distance to local government boundaries (municipal and school district). Grayed out metropolitan areas do not have a statistically significant spatial RD coefficient at the 5% confidence level.

Appendix Tables

Table A.1: Average segregation in metro areas, tract-level measure of segregation

| | Black | | | | Hispanic | | | | Asian | | | |
|---|-------|-------|-------|-------|----------|-------|-------|-------|-------|-------|-------|-------|
| | 1990 | 2000 | 2010 | 2020 | 1990 | 2000 | 2010 | 2020 | 1990 | 2000 | 2010 | 2020 |
| Minority share | 0.125 | 0.129 | 0.13 | 0.132 | 0.101 | 0.139 | 0.179 | 0.203 | 0.03 | 0.041 | 0.053 | 0.068 |
| Isolation | 0.425 | 0.379 | 0.334 | 0.303 | 0.209 | 0.26 | 0.297 | 0.309 | 0.072 | 0.094 | 0.117 | 0.144 |
| Segregation | 0.356 | 0.3 | 0.247 | 0.207 | 0.132 | 0.154 | 0.157 | 0.144 | 0.045 | 0.057 | 0.069 | 0.084 |
| <i>Panel A: County segregation</i> | | | | | | | | | | | | |
| Between counties | 0.049 | 0.049 | 0.044 | 0.038 | 0.017 | 0.02 | 0.021 | 0.02 | 0.005 | 0.007 | 0.01 | 0.013 |
| Within counties | 0.307 | 0.251 | 0.203 | 0.17 | 0.114 | 0.134 | 0.136 | 0.124 | 0.041 | 0.05 | 0.06 | 0.071 |
| <i>Panel B: City segregation</i> | | | | | | | | | | | | |
| Between cities | 0.118 | 0.114 | 0.1 | 0.087 | 0.044 | 0.055 | 0.058 | 0.057 | 0.012 | 0.018 | 0.024 | 0.032 |
| Within cities | 0.238 | 0.187 | 0.147 | 0.12 | 0.088 | 0.099 | 0.099 | 0.088 | 0.034 | 0.039 | 0.045 | 0.052 |
| <i>Panel C: School district segregation</i> | | | | | | | | | | | | |
| Between school districts | 0.116 | 0.111 | 0.097 | 0.084 | 0.046 | 0.059 | 0.062 | 0.061 | 0.012 | 0.02 | 0.027 | 0.036 |
| Within school districts | 0.24 | 0.189 | 0.15 | 0.123 | 0.085 | 0.095 | 0.094 | 0.083 | 0.033 | 0.037 | 0.043 | 0.049 |
| Between SAZs | — | — | — | 0.061 | — | — | — | 0.042 | — | — | — | 0.026 |
| Within SAZs | — | — | — | 0.059 | — | — | — | 0.046 | — | — | — | 0.027 |

Notes: Estimates based on census tract data. Isolation is the mean share of minority group residents, conditional on being a minority. Segregation is the variance ratio index of segregation, an isolation index adjusted for the group's population share. Between-local government segregation decompositions based on the discussion in section 3.5. SAZ = School Attendance Zone. Between-SAZ segregation decomposition based on private data from Precisely for the school year 2020-21.

Table A.2: 20 most segregated and most integrated MAs for Hispanic households, 2020

| | | 2020 | | | | Change 1990-2020 | | |
|---|------|-------|----------|-------------|--------------------|------------------|-----------------|--------------------|
| | Rank | m | η^2 | η^{-2} | η^{-2}/η^2 | Δm | $\Delta \eta^2$ | $\Delta \eta^{-2}$ |
| <i>Panel A: Most segregated metro areas</i> | | | | | | | | |
| Reading, PA | 1 | 0.232 | 0.456 | 0.36 | 0.788 | 4.549 | 1.26 | 3.193 |
| Salinas, CA | 2 | 0.605 | 0.444 | 0.311 | 0.701 | 1.796 | 0.966 | 1.117 |
| Santa Cruz-Watsonville, CA | 3 | 0.348 | 0.408 | 0.181 | 0.445 | 1.71 | 1.001 | 1.372 |
| Chicago-Naperville-Elgin, IL-IN-WI | 4 | 0.233 | 0.375 | 0.122 | 0.325 | 2.125 | 0.907 | 1.61 |
| Oxnard-Thousand Oaks-Ventura, CA | 5 | 0.433 | 0.372 | 0.216 | 0.582 | 1.636 | 0.95 | 1.268 |
| Miami-Fort Lauderdale-Pompano Beach, FL | 6 | 0.459 | 0.369 | 0.17 | 0.459 | 1.649 | 0.738 | 0.813 |
| Yakima, WA | 7 | 0.507 | 0.368 | 0.181 | 0.491 | 2.12 | 0.865 | 1.093 |
| Springfield, MA | 8 | 0.195 | 0.363 | 0.21 | 0.578 | 2.602 | 0.84 | 1.869 |
| Los Angeles-Long Beach-Anaheim, CA | 9 | 0.446 | 0.363 | 0.131 | 0.361 | 1.284 | 0.902 | 1.039 |
| Naples-Marco Island, FL | 10 | 0.272 | 0.345 | 0 | 0.001 | 1.994 | 0.797 | 10 |
| Santa Maria-Santa Barbara, CA | 11 | 0.47 | 0.338 | 0.167 | 0.496 | 1.768 | 1.066 | 1.718 |
| Scranton-Wilkes-Barre, PA | 12 | 0.116 | 0.334 | 0.129 | 0.386 | 20.523 | 4.658 | 10 |
| Kennewick-Richland, WA | 13 | 0.335 | 0.327 | 0.118 | 0.362 | 2.522 | 0.863 | 1.068 |
| Allentown-Bethlehem-Easton, PA-NJ | 14 | 0.183 | 0.324 | 0.179 | 0.554 | 4.342 | 1 | 3.683 |
| Providence-Warwick, RI-MA | 15 | 0.141 | 0.32 | 0.167 | 0.523 | 3.594 | 1.388 | 2.264 |
| Trenton-Princeton, NJ | 16 | 0.217 | 0.318 | 0.121 | 0.382 | 3.598 | 1.253 | 2.674 |
| Milwaukee-Waukesha, WI | 17 | 0.116 | 0.318 | 0.055 | 0.172 | 3.241 | 1.412 | 2.911 |
| Bakersfield, CA | 18 | 0.549 | 0.313 | 0.205 | 0.654 | 1.963 | 0.791 | 0.987 |
| Dallas-Fort Worth-Arlington, TX | 19 | 0.293 | 0.298 | 0.083 | 0.279 | 2.224 | 0.91 | 1.734 |
| Boston-Cambridge-Newton, MA-NH | 20 | 0.118 | 0.298 | 0.189 | 0.636 | 2.558 | 1.111 | 1.945 |
| <i>Median of most segregated MAs</i> | 10.5 | 0.282 | 0.341 | 0.169 | 0.475 | 2.174 | 0.958 | 1.726 |
| <i>Panel B: Most integrated metro areas</i> | | | | | | | | |
| Bremerton-Silverdale-Port Orchard, WA | 165 | 0.088 | 0.073 | 0.006 | 0.079 | 2.698 | 1.838 | 2.549 |
| Pensacola-Ferry Pass-Brent, FL | 164 | 0.064 | 0.076 | 0 | 0 | 3.54 | 1.601 | 0.064 |
| Olympia-Lacey-Tumwater, WA | 163 | 0.098 | 0.079 | 0.005 | 0.067 | 3.277 | 1.628 | 2.348 |
| Clarksville, TN-KY | 162 | 0.092 | 0.083 | 0.017 | 0.203 | 3.069 | 1.51 | 0.771 |
| Jacksonville, FL | 161 | 0.102 | 0.086 | 0.004 | 0.048 | 4.165 | 1.824 | 6.821 |
| Virginia Beach-Norfolk-Newport News, VA-NC | 160 | 0.075 | 0.086 | 0.007 | 0.083 | 3.391 | 2.346 | 1.932 |
| Spokane-Spokane Valley, WA | 159 | 0.063 | 0.086 | 0.004 | 0.045 | 3.318 | 1.213 | 1.948 |
| Ann Arbor, MI | 158 | 0.056 | 0.087 | 0.003 | 0.039 | 2.749 | 1.881 | 0.679 |
| Palm Bay-Melbourne-Titusville, FL | 157 | 0.112 | 0.089 | 0 | 0 | 3.643 | 1.409 | 10 |
| Kalamazoo-Portage, MI | 156 | 0.056 | 0.091 | 0.009 | 0.102 | 3.194 | 1.41 | 3.667 |
| Fayetteville, NC | 155 | 0.127 | 0.092 | 0.007 | 0.072 | 3.161 | 1.594 | 0.503 |
| Hagerstown-Martinsburg, MD-WV | 154 | 0.059 | 0.094 | 0.003 | 0.029 | 8.426 | 1.799 | 10 |
| Eugene-Springfield, OR | 153 | 0.099 | 0.094 | 0.008 | 0.08 | 4.066 | 1.64 | 10 |
| Albany-Schenectady-Troy, NY | 152 | 0.059 | 0.097 | 0.023 | 0.232 | 3.95 | 1.668 | 4.284 |
| Gainesville, FL | 151 | 0.115 | 0.097 | 0.002 | 0.016 | 3.369 | 1.437 | 0.992 |
| Lansing-East Lansing, MI | 150 | 0.068 | 0.099 | 0.023 | 0.237 | 1.902 | 0.992 | 1.21 |
| Laredo, TX | 149 | 0.952 | 0.101 | 0.002 | 0.023 | 1.014 | 0.754 | 0.111 |
| Tallahassee, FL | 148 | 0.079 | 0.103 | 0.004 | 0.039 | 3.457 | 0.982 | 3.872 |

| | | | | | | | | |
|--------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Killeen-Temple, TX | 147 | 0.24 | 0.105 | 0.007 | 0.067 | 1.956 | 0.772 | 1.854 |
| Seattle-Tacoma-Bellevue, WA | 146 | 0.112 | 0.108 | 0.018 | 0.168 | 3.795 | 2.286 | 5.78 |
| <i>Median of most integrated MAs</i> | 155.5 | 0.09 | 0.092 | 0.006 | 0.067 | 3.343 | 1.598 | 2.148 |

Notes: Rank: MA segregation rank out 140 large MAs with at least 5% Hispanic. Changes between 1990-2020 denoted by $\Delta x = x_{2020}/x_{1990}$. Values of 10 and -10 indicate more than ten-fold increases and decreases, respectively.

Table A.3: 20 most segregated and most integrated MAs for Asian households, 2020

| | 2020 | | | | | Change 1990-2020 | | |
|---|------|-------|----------|-------------|--------------------|------------------|-----------------|--------------------|
| | Rank | m | η^2 | η^{-2} | η^{-2}/η^2 | Δm | $\Delta \eta^2$ | $\Delta \eta^{-2}$ |
| Panel A: Most segregated metro areas | | | | | | | | |
| Trenton-Princeton, NJ | 1 | 0.126 | 0.308 | 0.182 | 0.589 | 4.214 | 3.012 | 4.996 |
| Raleigh-Cary, NC | 2 | 0.071 | 0.285 | 0.015 | 0.052 | 4.626 | 2.709 | 4.348 |
| New York-Newark-Jersey City, NY-NJ-PA | 3 | 0.125 | 0.267 | 0.069 | 0.258 | 2.573 | 1.482 | 3.872 |
| Los Angeles-Long Beach-Anaheim, CA | 4 | 0.17 | 0.248 | 0.118 | 0.475 | 1.665 | 1.388 | 2.656 |
| San Jose-Sunnyvale-Santa Clara, CA | 5 | 0.384 | 0.245 | 0.142 | 0.581 | 2.338 | 1.392 | 2.279 |
| Dallas-Fort Worth-Arlington, TX | 6 | 0.081 | 0.243 | 0.081 | 0.333 | 3.408 | 2.209 | 8.144 |
| San Francisco-Oakland-Berkeley, CA | 7 | 0.282 | 0.239 | 0.108 | 0.451 | 1.794 | 1.097 | 1.847 |
| Atlantic City-Hammonton, NJ | 8 | 0.081 | 0.223 | 0.038 | 0.172 | 3.963 | 2.116 | 7.308 |
| Chicago-Naperville-Elgin, IL-IN-WI | 9 | 0.072 | 0.212 | 0.063 | 0.298 | 2.357 | 1.475 | 3.141 |
| Fayetteville-Springdale-Rogers, AR | 10 | 0.057 | 0.211 | 0.023 | 0.107 | 8.579 | 2.099 | 7.696 |
| Houston-The Woodlands-Sugar Land, TX | 11 | 0.084 | 0.21 | 0.055 | 0.263 | 2.491 | 1.578 | 1.94 |
| Stockton, CA | 12 | 0.186 | 0.208 | 0.042 | 0.201 | 1.602 | 0.685 | 1.218 |
| Atlanta-Sandy Springs-Alpharetta, GA | 13 | 0.066 | 0.207 | 0.036 | 0.173 | 3.986 | 2.493 | 4.997 |
| Ann Arbor, MI | 14 | 0.091 | 0.194 | 0.056 | 0.286 | 2.217 | 1.439 | 2.716 |
| Sacramento-Roseville-Folsom, CA | 15 | 0.158 | 0.192 | 0.073 | 0.378 | 2.134 | 1.026 | 1.726 |
| Harrisburg-Carlisle, PA | 16 | 0.053 | 0.184 | 0.03 | 0.161 | 4.823 | 2.106 | 9.865 |
| Boston-Cambridge-Newton, MA-NH | 17 | 0.087 | 0.178 | 0.067 | 0.375 | 3.063 | 1.181 | 3.045 |
| Minneapolis-St. Paul-Bloomington, MN-WI | 18 | 0.072 | 0.178 | 0.041 | 0.228 | 2.904 | 0.903 | 2.66 |
| Austin-Round Rock-Georgetown, TX | 19 | 0.072 | 0.176 | 0.032 | 0.182 | 3.328 | 1.685 | 6.136 |
| San Diego-Chula Vista-Carlsbad, CA | 20 | 0.129 | 0.176 | 0.04 | 0.228 | 1.743 | 1.106 | 1.766 |
| <i>Median of most segregated MAs</i> | 10.5 | 0.086 | 0.21 | 0.055 | 0.261 | 2.738 | 1.478 | 3.093 |
| Panel B: Most integrated metro areas | | | | | | | | |
| Reno, NV | 47 | 0.066 | 0.067 | 0 | 0.004 | 1.823 | 0.863 | 1.738 |
| Bremerton-Silverdale-Port Orchard, WA | 46 | 0.063 | 0.069 | 0.009 | 0.125 | 1.575 | 1.286 | 1.352 |
| Bridgeport-Stamford-Norwalk, CT | 45 | 0.054 | 0.073 | 0.008 | 0.114 | 2.659 | 1.043 | 2.399 |
| Salt Lake City, UT | 44 | 0.059 | 0.079 | 0.005 | 0.063 | 2.238 | 0.927 | 0.923 |
| Boulder, CO | 43 | 0.051 | 0.088 | 0.003 | 0.032 | 2.098 | 1.213 | 0.938 |
| Olympia-Lacey-Tumwater, WA | 42 | 0.07 | 0.088 | 0.017 | 0.192 | 1.937 | 1.049 | 1.474 |
| Salinas, CA | 41 | 0.066 | 0.093 | 0.024 | 0.254 | 0.919 | 0.88 | 0.991 |
| Santa Rosa-Petaluma, CA | 40 | 0.05 | 0.095 | 0.012 | 0.123 | 1.914 | 1.984 | 1.919 |
| Oxnard-Thousand Oaks-Ventura, CA | 39 | 0.079 | 0.098 | 0.016 | 0.164 | 1.617 | 0.989 | 3.522 |

| | | | | | | | | |
|--------------------------------------|------|-------|-------|-------|-------|-------|-------|----------|
| Las Vegas-Henderson-Paradise, NV | 38 | 0.114 | 0.102 | 0 | 0 | 3.452 | 2.091 | ∞ |
| Modesto, CA | 37 | 0.071 | 0.107 | 0.014 | 0.135 | 1.442 | 0.683 | 1.001 |
| Gainesville, FL | 36 | 0.055 | 0.125 | 0.01 | 0.078 | 2.596 | 1.171 | 3.341 |
| College Station-Bryan, TX | 35 | 0.057 | 0.131 | 0.03 | 0.226 | 2.004 | 0.413 | 1.268 |
| Albany-Schenectady-Troy, NY | 34 | 0.052 | 0.132 | 0.029 | 0.221 | 4.104 | 1.626 | 3.459 |
| Merced, CA | 33 | 0.077 | 0.138 | 0.035 | 0.254 | 0.971 | 0.457 | 0.897 |
| Portland-Vancouver-Hillsboro, OR-WA | 32 | 0.077 | 0.141 | 0.029 | 0.203 | 2.304 | 1.461 | 2.699 |
| Santa Maria-Santa Barbara, CA | 31 | 0.061 | 0.143 | 0.036 | 0.249 | 1.493 | 2.158 | 3.201 |
| Riverside-San Bernardino-Ontario, CA | 30 | 0.08 | 0.15 | 0.047 | 0.315 | 2.216 | 1.708 | 4.434 |
| Bakersfield, CA | 29 | 0.053 | 0.152 | 0.044 | 0.29 | 1.94 | 0.936 | 0.956 |
| Vallejo, CA | 28 | 0.17 | 0.155 | 0.03 | 0.192 | 1.426 | 0.884 | 0.608 |
| <i>Median of most integrated MAs</i> | 37.5 | 0.064 | 0.104 | 0.016 | 0.178 | 1.939 | 1.046 | 1.413 |

Notes: Rank: MA segregation rank out 140 large MAs with at least 5% Asian. Changes between 1990-2020 denoted by $\Delta x = x_{2020}/x_{1990}$. Values of 10 and -10 indicate more than ten-fold increases and decreases, respectively.

