The Daily Ballet of Temporary Integration: Spatio-Temporal Segregation Dynamics in Metropolitan U.S.A.*

ELIJAH KNAAP, University of California, Riverside
SERGIO REY, University of California, Riverside
RENAN XAVIER CORTES, University of California, Riverside
WEI KANG, University of California, Riverside

A recent wave of scholarship examines the ways that daily activity spaces contribute to the experience of racial and ethnic segregation in large cities. In this paper, we take a different approach, leveraging administrative data on the residential and workplace locations of employees in large American metropolitan regions to examine daily and annual fluctuation in multiscalar segregation. In each MSA we measure racial and ethnic segregation in local residential and workplace "egohoods," defined as the set of census blocks accessible within a 25 minute walk along the pedestrian transportation network. We then construct multiscalar segregation profiles by increasing the travel bandwidth and re-computing our segregation index. Measuring the gap between residential and workplace segregation statistics at each scale reveals the extent that residential locations play in exacerbating urban segregation, and the role that daily commuting plays in overcoming these patterns to achieve temporary integration. Repeating this process for each year between 2010 and 2017, we quantify the variance in segregation levels over time for each location and at each spatial scale. Our results show that during work hours, the vast majority of cities are highly racially integrated at all spatial scales, thanks to the cosmopolitan nature of urban labor markets, but daily transport patterns and persistent residential segregation work to overcome this temporary state of togetherness, leaving most neighborhoods deeply segregated at night and on the weekends, particularly at smaller spatial scales. We interpret these findings in light of recent COVID-related trends that include increased teleworking and a return to suburbanization.

Keywords: spatial analysis, multiscalar, segregation dynamics, racial inequality

INTRODUCTION

Racial segregation is a lamented but persistent feature of most neighborhoods in urban America. The negative consequences of segregation have been studied in great detail over the last several decades, with most scholars agreeing that continuing segregation contributes to persistent economic inequality between major racial groups. Despite lively interest and a great deal of research, however, there remains much unknown about the spatial scales or time periods over which segregation changes, and the ways these changes impact the daily lives of metropolitan residents. Recent work using activity tracking, e.g. by Sampson & Levy (2020) and Kwan (2015) helps demonstrate that the *experience* of segregation can vary dramatically throughout the course of a day, thanks to disparate activity patterns, but while these studies are illuminating, we argue there is a need to understand how these trends are evolving over moderate time spans, for example how the experience of daily segregation changes from over the course of a typical day, or from year to year–and over which spatial scales.

To address this gap, we use eight years of annual Census block-level data from the thirty largest Metropolitan Statistical Areas (MSAs) in the United States to examine the space-time dynamics of residential and workplace segregation. Following Kim & Hipp (2019), we rely on the concept of egohoods, which we term "neighborhoods" for home locations and "laborhoods" for workplace locations. We de-

*Corresponding author can be reached at knaap@ucr.edu. This work is supported by NSF Grant #1831615 Scalable Geospatial Analytics for Social Science Research

fine a local egohood as the set of census blocks reachable within a specified walk commute along the pedestrian transportation network from the centroid of a focal block. Proceeding, we first construct multiscalar segregation profiles for every MSA in the United States for both home and workplace egohoods. Following prior work, we use the Spatial Information Theory Index ($\tilde{H}$) with increasingly large bandwidths for our egohoods.

We repeat this process for each year between 2010 and 2017, measuring the difference between home and workplace segregation at each scale. This yields a rich set of analytics that describe how measured levels of segregation fluctuate over space and time for each MSA at multiple spatial and temporal scales. These metrics are easily interpretable as a set of data visualizations, the first of which are line graphs, where the shape of each segregation profile describes the geographic scale of neighborhood and laborhood segregation in each MSA, and the distance between each curve describes the increase or decrease in segregation at different scales between consecutive years. Meanwhile, the distance between the neighborhood and laborhood curves describes the changing context of segregation individuals experience over the course of a typical day. To capture this distance between neighborhood and laborhood curves, we introduce the *segregation commute gap* statistic, which quantifies the role that daily commute patterns play in maintaining segregation. Finally, we use the coefficient of variation to measure annual fluctuation in segregation at each scale, and together these measures provide unique insight into the pulse of American cities over different time periods and spatial scales.

Our results show that the experience of segregation is highly dependent on space and time, and these factors interact uniquely for each demographic group in each metropolitan region of our study. Most cities are segregated by night and integrated by day, a pattern that appears to be changing little over time. When segregation changes, it does so in heterogeneous ways depending on the social and economic characteristics of each metro, but there is some evidence that residential segregation is most variable at smaller scales whereas workplace segregation is most variable at larger ones. In what follows we describe the importance of considering a dynamic look at urban segregation and after the presentation of our results we unpack their implications for both the science and policy of cities.

SEGREGATION THROUGH SPACE AND TIME

Although there is an expansive literature on both segregation measurement techniques and their applications, the body of work focusing on segregation *dynamics* (in either spatial, temporal, or spatiotemporal dimensions) is dramatically smaller by comparison. Most existing work on temporal dynamics highlights long-term trends over the course of two or more decades (Massey, 2020), work on spatial dynamics is limited to a small handful of empirical studies (Fowler, 2016; Reardon et al., 2009, 2008), and work on *spatiotemporal* dynamics is an even smaller cross-section of the research record.

Temporal segregation dynamics examine how one or more segregation measures change over time for a given (static) location. A common strategy for studying temporal segregation dynamics is to examine how the value of a segregation index changes over one or more time periods using decennial census data (Madden & Ruther, 2018; Massey, 1978; Massey, 2020), or other long-term databases such as the Panel Study of Income Dynamics (Lee, 2017). More recent work focuses on much higher temporal granularity, using high-resolution data to examine temporal trends over the course of a given day. For example Dannemann et al. (2018) use cell phone Data, Sampson & Levy (2020) and Wang et al. (2018) use social media data, and Park & Kwan (2018) and Zhang et al. (2018) use GPS-based temporal activity tracking measure fluctuating patterns in exposure to segregated spaces throughout the course of a day. In France, Le Roux et al. (2017) use travel diary data for 25,000 Parisians to study segregated activity spaces. This work is insightful but limited by two critical drawbacks. First, the focus on decennial or daily fluctuations in segregation statistics overlooks the relevance of critical moderate-term change on an *annual basis*. Second, the use of novel data sources such as social media posts and cellphone tracking information, while innovative, introduce a host of issues regarding data quality that include questions of representativeness, measurement error, and potential for unexplored bias, given that the data are taken from nonrandom samples.

Spatial segregation dynamics examine how one or more segregation measures change over a range of spatial scales for a given (static) timeframe. Early work on the role of space in the measurement of segregation is given by Reardon et al. (2008) who introduce the multiscalar profile showing how the multigroup Spatial Information Theory index changes value as a function of the distance used to define a local neighborhood. Following, a major contribution is given by Lee et al. (2008), who calculate multiscalar segregation profiles for 100 metropolitan regions in the United States, finding that the "northeast and the South are more micro-segregated than their Western counterparts, usually because of smaller-scale, localized fluctuations in racial composition." Catney (2018) follows a similar strategy for the British context, constructing multiscalar profiles for Isolation and Dissimilarity. Both studies rely on Euclidean distance calculations, concluding that "alternative proximity functions based on population density or travel time could help build social distance into our approach, although implementation of these metrics remains daunting." (Lee et al., 2008, p. 17).

Östh et al. (2015) share that perspective, advocating a K-nearest-neighbors approach to calculate local egocentric neighborhoods, focusing on population size rather than distance threshold to define the scale of a local neighborhood. Today, however, the computational burden of constructing these metrics is considerably lower, and both travel network data (such as OpenStreetMap) and fast routing algorithms are both publicly available and easy to use. Roberto (2018) provides a useful example of more complex and behaviorally-realistic ways of incorporating space in segregation indices by assuming that interpersonal exposure is conditioned on travel networks, showing the clear impact that considering infrastructure can play in segregation measurement and the motivation for incorporating network analysis into spatial segregation metrics.

Spatiotemporal segregation dynamics examine how segregation measures fluctuate across spatial scales for multiple time frames. The literature on spatio-temporal segregation dynamics is sparse, but a classic example is given by Massey & Hajnal (1995) who examine how the Dissimilarity and Isolation statistics change from 1900 to 1990 over four geographic scales. More recently, Charles (2003) expanded on this work, using a similar strategy to examine temporal variation at the MSA level for multiple measures and racial groups over the 1980-2000 period. These studies highlight modest but substantive declines for certain aspects of black segregation, but increases for other indexes and racial groups. Most often, however, scholarship in this vein relies on data collected at coarse spatial and temporal scales, typically tract-level decennial census data. In an important innovation in spatiotemporal dynamics, Reardon et al. (2009) calculated multiscalar segregation profiles and examined differences between profiles generated from 1990 and 2000. Following, Fowler (2016) used a similar strategy to calculate segregation profiles for decennial census data in the Seattle metro region.

Here, we extend these works to include more locations, annual-level frequency, and measurements for both home and work segregation statistics.

NEIGHBORHOODS AND LABORHOODS: TEMPORAL PARTITIONING OF URBAN SPACE

With respect to temporal segregation dynamics, we argue a critical distinction on the experience of urban space is the difference between daytime population centers and nighttime population centers. Aside from commutes, errands, and other activities, adults spend the vast majority of their day time in their workplace locations, whereas children spend it at their local schools. At night and on the weekends, both children and adults spend time in their homes (or using their home locations to base their activity spaces). Rather than measuring the full scope of individual-level activity patterns, therefore, we argue that developing measures based on home and workplace locations—what we term "neighborhoods and laborhoods"—provides a revealing examination of temporal changes in the experience of segregation, for which data are both readily available and well-measured. We are not the first to observe the importance of contrasting home and workplace segregation; indeed, "the issue of nighttime and daytime populations is of growing interest in measuring segregation... [and Östh, Clark, and Malmberg] note that using workplace data it would be possible to measure what are essentially daytime levels of segregation" (Östh et al., 2015, p. 41).

Toward these ends, some existing work examines daytime/workplace segregation and its implications for studying urban environments. For example Ellis et al. (2004) show that workplace segregation was considerably lower than residential segregation in 1990 Los Angeles, and the difference varied across racial groups, and Wang (2010) use long-form census data from 2000 to examine the impact of labor market segregation for Chinese immigrants in the Bay Area. In the European context, Tammaru et al. (2016) use Swedish long-form data to study residential and workplace segregation for recent immigrants, using regression models to demonstrate a weak connection between the two. Further, they show that residential segregation and intermarriage among new immigrants in Sweden has differential effects for men than for women. Regardless of the specific findings in the Swedish context, Tammaru et al. (2016)'s work demonstrates the clear need to understand the dynamic connection between workplace and residential segregation levels.

Our review of the limited scholarship on spatiotemporal segregation dynamics shows existing work embodies a tradeoff between spatial and temporal precision. When studies examine detailed spatial or temporal changes in segregation, they do so for a single metropolitan area and/or limited time-scales; when high-resolution temporal data are used, spatial coverage is neglected, given high financial and labor costs for data collection; when high resolution spatial data are used, temporal coverage reduces to decadal censuses. Furthermore, when more realistic and measures such as network distance are incorporated into the analysis, spatial and temporal scopes reduce even further. We are interested in the ways that *daily* levels of segregation have changed over multiple spatial scales, and in turn, how those daily measures (at each scale) evolve on an *annual* basis. We also want to understand whether these patterns are consistent in metropolitan regions across the country and for different ethnic groups.

Toward these goals we find several areas for improvement. In the spatial case, there is a need for measures that incorporate more realistic concepts of neighborhoods and activity spaces. In particular, the literature indicates a need for measures that account for topography, and transportation networks. Progress toward these ends is provided by Roberto (2018), but remains limited in scope and is not reproducible. Here, we provide a computational method for measuring segregation that uses network analysis to construct "egohoods," (Hipp et al., 2012) which measure bespoke neighborhoods at several scales, and we provide simple, open-source code for replicating our method and applying it elsewhere. Further, the literature makes clear there is a need for (1) more reliable sources of temporal variation in local contexts, and (2) meso-level segregation measures that can capture changes at both daily and annual scales. The limited spatio-temporal segregation analyses that do exist rely on decennial census data and examine only two time periods at a coarse resolution. What remains is a gap in current knowledge about spatio-temporal segregation dynamics at annual and daily scales. We provide such an analysis here.

MEASURING SEGREGATION AT MULTIPLE SPATIAL AND TEMPORAL SCALES

To examine spatial variation in segregation, we rely on the notion of a multiscalar segregation profile, introduced by Reardon et al. (2008) and applied by Lee et al. (2008) and Fowler (2016). The experience of segregation in a metropolitan region depends not only on the local demography but also its built environment. Urban spatial structure, land use policy, and political economy can have a profound effect on urban segregation patterns by helping to create the proverbial "wrong side of the tracks," a euphemism in American English used to describe a neighborhood of ill repute. In this context, such a euphemism is a reminder that train tracks, empty lots, abandoned buildings, etc, are often demarcators–either natural or intentional–of different social delineations in the city. Given this reality, we argue that conceptually-realistic measures of segregation should seek to incorporate physical measures of the built environment, most importantly pedestrian street-network connectivity, which is the fundamental circulatory system that supports an urban populous (Roberto, 2018). Street connectivity patterns vary tremendously across the U.S., and indeed the world, (Boeing, 2018), so our multiscalar segregation profiles use pedestrian network distance to construct egohoods that define each scale in the profile.

We construct egohoods by collecting data from OpenStreetMap for each metropolitan area and using the Python package `pandana` to process it into a routable pedestrian network by removing impassable portions such as highways and interstates and including penalties for intersection crossings (contributors, 2017; Foti et al., 2012). We then use `pandana` to calculate local egohoods for each census block in the study area, subject to a triangular distance decay function. This, effectively, transforms the block-level data into a population accessibility surface, where each block no longer represents solely the population inside, but rather the population one would likely encounter in that block's local environment, discounted by distance. For ease of calculation, each census block is represented by its mathematical center, and assigned to the nearest node in the transportation network.

Conceptually, this step is akin to the pycnophylactic smoothing performed by Reardon et al. (2008) and Fowler (2016), except that our approach uses a different decay function,[1] measures network rather than euclidean distance, and preserves the original topology rather than interpolating the data

[1] Here we use a simple triangular decay function that discounts observations as a linear function of (network) distance, though we also test exponential decay functions, and they have a negligible effect on our results

down to a regular grid. Using this alternative strategy, we answer the call by Reardon et al. (2008, p. 509) to address whether features such as topography or "the nature and scale of tertiary street networks, for example, play a role in shaping racial housing patterns," and remove the assumption "that all people can move freely throughout their local environments despite the irregular distribution of highways, railroad tracks, parks, bodies of water, and other barriers" (Lee et al., 2008, p. 19).

Data

For each of the 30 largest metropolitan regions in the USA, we collect data from the Origin-Destination Employment Statistics (LODES) tabulations from the U.S. Census Bureau's Longitudinal Employer Household Dynamics (LEHD) dataset (U.S. Census Bureau, 2020). Unlike decennial census data, LODES data are tabulated annually from administrative records and provide counts of employees at the census-block level for both home and workplace locations. Since 2002, the LODES data include information on worker race and ethnicity, among other variables. Together, these features mean that LODES data provide a unique opportunity to study the temporal fluctuation in metropolitan segregation. Since data are tabulated for both workplace and residential locations of workers, and are released annually, they provide *two* temporal scales rarely seen in the segregation literature: examining differences between workplace and residential segregation provides insight into daily variation whereas comparisons between successive datasets permits insight into annual variation in segregation. Furthermore, since the data are tabulated at the census block level, rather than the more traditionally-used tracts or block-groups, these data provide an unprecedented level of spatial and temporal resolution.

The advantages to LODES data do not come without tradeoffs, however. Since the data refer only to employed populations, our inference on metropolitan segregation extends only to the workforce and will not account for children, retired/elderly, or other systematic variation in unemployed populations. Further, since LODES data are tabulated and modeled from administrative data, "not derived from a probability-based sample, no sampling error measures are applicable" (U.S. Census Bureau, 2020). This means that while the Census bureau has worked to mitigate errors in the data, they are nonetheless subject to unknown nonsampling error that could result from "misreported data, late reporters whose records are missing and imputed, and geographic/industry edits and imputations." Despite these limitations, the resolution offered by LODES is an acceptable trade off, given certain reservations about limiting the scope of inference from our results.

Computing Segregation Profiles

To measure spatial segregation dynamics, we adopt the multiscalar segregation profile, which "describes both the absolute level of segregation at any scale and the rate of change in segregation level with scale" (Reardon et al., 2008, p. 497). These profiles are "constructed by plotting segregation level against scale," thus requiring a measure that is sensitive to geographic scale. We therefore adopt the spatial information theory statistic as our measure of segregation. "The index $\tilde{H}$ is a measure of how much less diverse individuals' local environments are, on average, than is the total population of region," and reaches its maximum of 1 only when "each individual's local environment is monoracial"

(Reardon et al., 2008, p. 512). Following the notation of Reardon & O'Sullivan (2004), we calculate the index using three equations.

$$\tilde{\pi}_{pm} = \frac{\int_{q \in R} \tau_{qm} \phi(p, q) dq}{\int_{q \in R} \tau_q \phi(p, q) dq} \tag{1}$$

Equation 1 describes the proportion of population group m at location p, with τ_p and τ_{pm} as the total population count and population count of group m, respectively. In our case, p is the local egohood, measured from the centroid of each census block, and $\phi(p, q)$ is a triangular function of the pedestrian network distance between p and q. Unlike Reardon et al. (2008) and Fowler (2016) who interpolate their data to a regular grid using a euclidean kernel simulating a continuous density surface, our approach fixes observations to the transportation grid and uses network impedance as the distance measure[2]. This has the effect of transforming the data into a network-based *accessibility* surface, common in transportation modeling and regional science (Hansen, 1959; Levinson, 1998). Here, $\tilde{\pi}_{pm}$ represents the population in group m, accessible from each block, divided by the total population accessible from each block, and $\phi(p, q)dq$ is a decay function of shortest network distance (Foti et al., 2012)

$$\tilde{E}_p = -\sum_{m=1}^{M} (\tilde{\pi}_{pm}) \log_M (\tilde{\pi}_{pm}) \tag{2}$$

Equation 2 describes the entropy of the local egohood of p, where M indicates the number of race groups in the population. In this case $M = 2$ for all cases, since we compute two-group, rather than multi-group segregation statistics given the limitations of our data[3].

$$\tilde{H} = 1 - \frac{1}{TE} \int_{p \in R} \tau_p \tilde{E}_p dp \tag{3}$$

Equation 3 is the Spatial Information Theory statistic given by Reardon & Firebaugh (2002) and Reardon & O'Sullivan (2004) where T is the total population and E is the overall regional entropy. To build multiscalar segregation profiles, we vary the bandwidth parameter in Equation 1 between 0m and 5000m in intervals of 500 meters[4]. We perform all calculations using the open-source Python package `segregation`, distributed as part of the Python Spatial Analysis Library (PySAL) (Cortes, Rey, et al., 2019; Rey & Anselin, 2010)[5].

[2] Since we use the pedestrian network to approximate neighborhood distance, impedance is equivalent to distance, since we assume pedestrian travel is constant-speed along an uncongested network

[3] LODES data do not cross-tabulate race and ethnicity so Hispanic/non-Hispanic segregation needs to be calculated separately than racial segregation

[4] Note that in the case of $\tilde{H}0$ (i.e. an egohood bandwidth of zero), the measure is equivalent to the block-level *aspatial* information theory index

[5] Our analysis is fully reproducible and the code is available on Github and upon request

Measuring Segregation Dynamics

We proceed to measure spatial dynamics by calculating multiscalar profiles and plotting the results as line graphs. The multiscalar profile can be summarized using the macro/micro segregation ratio which measures "proportion of micro-segregation that is due to residential patterns at the macro-scale or larger" (Reardon et al., 2008). To measure daily temporal dynamics we introduce a measure we call the *commute gap*, CG. The commute gap is the ratio of the difference in residential segregation minus workplace segregation over residential segregation, and quantifies how much residential segregation is accounted by the gap between workplace and home place.

$$CG = \frac{\tilde{H}_R - \tilde{H}_W}{\tilde{H}_R} \tag{4}$$

Larger numbers indicate a greater gap between residential segregation and workplace segregation and imply a greater role of transportation in the maintenance of segregation. A different way of interpreting the number is the share of regional segregation attributable to daily commuting patterns; if every employee in the region worked from home, the difference between $\tilde{H}_R$ and $\tilde{H}_W$ would be zero, as would the measure itself. To measure annual temporal dynamics we use the coefficient of variation, c_v to capture volatility in the annual measurement of $\tilde{H}$, and we examine spatiotemporal dynamics by showing how c_v changes at each spatial scale. We follow a similar strategy with CG to understand daily spatiotemporal dynamics.

SPATIO-TEMPORAL SEGREGATION DYNAMICS IN LARGE U.S. METROS

Figure 1 and Figure 2 show that, in general, there is more variation in black/white segregation and levels are typically higher than Hispanic/non-Hispanic segregation at every scale, however, there are notable exceptions, most of which are in the sunbelt; the metropolitan regions of Phoenix, Las Vegas, Riverside, San Diego and San Antonio, for instance, all exhibit greater Hispanic/non-Hispanic residential segregation than black/white residential segregation. The racial and ethnic patterns are not always uniform, however. In Los Angeles, for example, the segregation profiles for black/white and Hispanic/non-Hispanic populations cross twice, indicating that black segregation is greater at small and large scales, but Hispanic segregation is greater at moderate scales. Spatial dynamics such as these reinforce the importance of geographic scale in the scholarship on racial segregation and inequality. Miami's Hispanic segregation profile in Figure 2 stands alone as a clear outlier with $\tilde{H}$ levels far above other metropolitan regions for both workplace and residential segregation at nearly every scale. Another clear pattern is that there is more variance both in segregation levels overall and the slopes of black/white profiles as compared to Hispanic/non-Hispanic profiles, for both residential and workplace segregation.

Spatial Dynamics

Following Reardon et al. (2008), we calculate macro/micro segregation ratios by dividing the $\tilde{H}4000$ measure by $\tilde{H}500$ measure. These statistics measure the share of small-scale segregation attributable to large-scale patterns and provide a general sense of each profile's shape. Higher

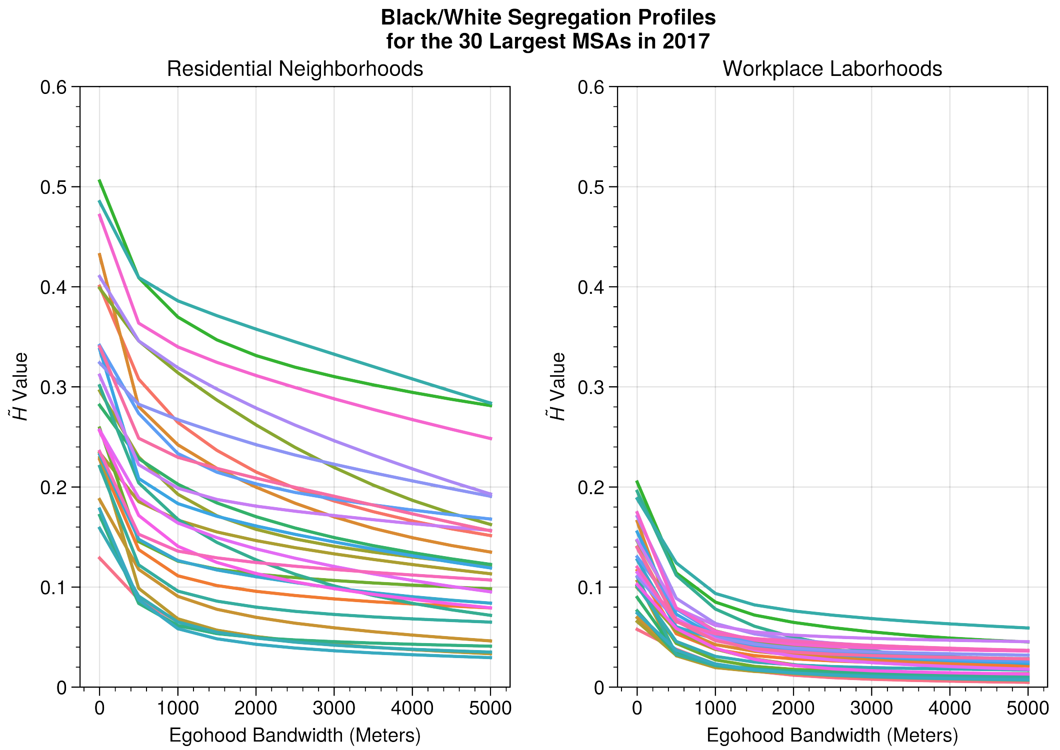


Figure 1: Black/White Segregation Profiles

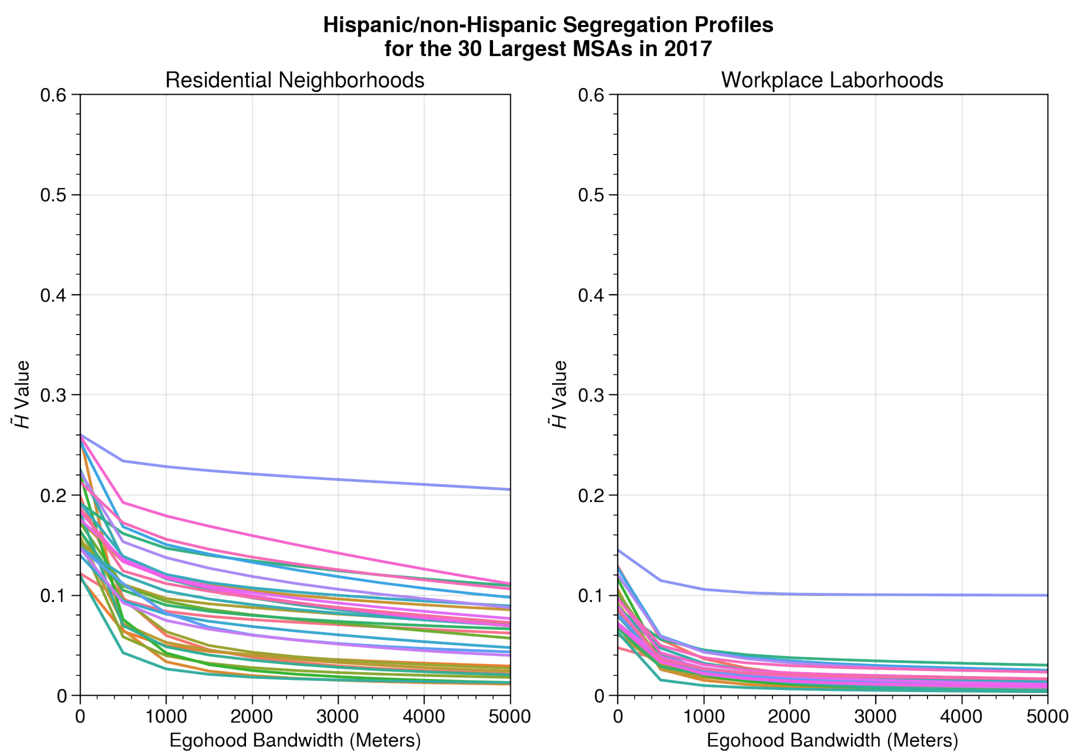


Figure 2: Hispanic/non-Hispanic Segregation Profiles

macro/micro ratios indicate flatter segregation profiles and metropolitan regions characterized by macro-scale segregation, whereas small rations indicate steeper profiles and metros with higher levels of micro-scale segregation. Macro/micro segregation ratios are shown in Table 2 and Table 3 for black/white and Hispanic/non-Hispanic segregation, respectively. The tables reveal two clear findings; first, in addition to fact that black/white segregation levels are typically much higher than Hispanic/non-Hispanic levels, so too are black/white segregation profiles typically considerably steeper than Hispanic/non-Hispanic profiles in each metro. Second, Tables 2, 3 show that there is little temporal variation in the macro/micro ratios, but there is some indication of ratios increasing over time, particularly for earlier years. Put differently, looking across the tables, there is some evidence that segregation profiles are flattening slightly and that segregation falls faster at small scales. Another way of describing this phenomenon is that large regional patterns of segregation are more stubborn than localized pockets.

Temporal Dynamics

At the daily temporal scale there is a great deal of variation in segregation, driven almost exclusively by residential segregation. That is, the near absolute dearth of daytime segregation in major American metropolitan areas means the areas that tend to have the largest daily fluctuations in measured segregation are those with the greatest levels of residential segregation (e.g. St. Louis and Detroit). At the annual temporal scale there is, generally, little variation in measured segregation levels. When there is change, it is typically at smaller scales, consistent with Lee et al. (2008)'s prediction regarding the stubbornness of segregation at larger scales. An alternative (though not mutually exclusive) explanation is the small scale variation may be related to overall economic dynamics than "true" changes in the spatial distribution of different racial groups. Since the LODES data capture employed populations, and most variation happens almost exclusively at small scales, we may also be capturing fluctuation in the existence of small firms.

To understand how much racial segregation is driven by the movement between home and workplace areas, we present commute gap statistics for each metro area in 2017 in Table 1, which is sorted in descending order by BlackCG. Among the top ten largest Black commute gap statistics, Florida cities appear three different times (Tampa, Orlando and Miami) revealing distinct patterning in the labor and residential markets in that state, with residential segregation accounting for greater than 80% of the separation between races. In contrast, among the ten lowest measures, California cities appear five times (Riverside, Los Angeles, San Francisco, San Diego, Sacramento) with residential segregation accounting for less than 70% of the regional segregation. Both Florida and California are heavy automobile-commuting states (Kane et al., 2020)[6], and their places at the top and bottom of the rankings (respectively) suggest that in addition to the harm of residential segregation Black Floridians may also suffer an additional burden of transport inequality, whereas Black Californians likely bear a smaller burden. For Hispanic/Latino Americans, the southwest region typically contributes the greatest commute-gap statistics, with some of the largest belonging to Dallas, San Antonio, Phoenix. The largest CG for Hispanic/Latino segregation, however, belongs to Chicago, a notable outlier in its region

[6] See also https://www.vitalsigns.mtc.ca.gov/commute-mode-choice and https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/planning/demographic/2019commuting.pdf

as most other midwestern metros appear near the bottom. Additional visualizations of commute gap statistics showing variation by spatial scale are available in the appendix

Metropolitan Region	Black $\mathbf{CG}_{1500}$	Black $\mathbf{H}_{1500}$	Hisp $\mathbf{CG}_{1500}$	Hisp $\mathbf{H}_{1500}$
Tampa-St. Petersburg-Clearwater, FL	0.905045	0.184105	0.788648	0.0837215
Orlando-Kissimmee-Sanford, FL	0.891678	0.155073	0.773486	0.0911297
Chicago-Naperville-Elgin, IL-IN-WI	0.854656	0.324515	0.851991	0.168661
Baltimore-Columbia-Towson, MD	0.837578	0.286834	0.422874	0.0317773
Cincinnati, OH-KY-IN	0.836765	0.236605	0.404976	0.0453254
Pittsburgh, PA	0.836187	0.218621	0.557244	0.0240313
Charlotte-Concord-Gastonia, NC-SC	0.835224	0.171291	0.676055	0.049562
Miami-Fort Lauderdale-West Palm Beach, FL	0.831452	0.254286	0.543837	0.224174
Denver-Aurora-Lakewood, CO	0.82341	0.118011	0.795481	0.0856158
New York-Newark-Jersey City, NY-NJ-PA	0.823026	0.218597	0.787342	0.103702
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.821345	0.29781	0.713015	0.126754
Seattle-Tacoma-Bellevue, WA	0.802022	0.0859493	0.63934	0.0207476
Atlanta-Sandy Springs-Roswell, GA	0.79697	0.214769	0.719858	0.067861
St. Louis, MO-IL	0.792354	0.34697	0.548579	0.0304873
San Antonio-New Braunfels, TX	0.789825	0.0778134	0.816369	0.110032
Detroit-Warren-Dearborn, MI	0.778496	0.371169	0.760362	0.105525
Dallas-Fort Worth-Arlington, TX	0.776597	0.124623	0.842442	0.107036
Boston-Cambridge-Newton, MA-NH	0.758146	0.17072	0.731145	0.140788
Houston-The Woodlands-Sugar Land, TX	0.750481	0.149392	0.8018	0.108852
Portland-Vancouver-Hillsboro, OR-WA	0.724019	0.0569727	0.684027	0.0448125
Las Vegas-Henderson-Paradise, NV	0.712825	0.0556657	0.740295	0.0786622
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.705842	0.187554	0.753508	0.065828
Sacramento–Roseville–Arden-Arcade, CA	0.688898	0.101536	0.633884	0.0437213
San Diego-Carlsbad, CA	0.659268	0.0535029	0.711557	0.139557
San Francisco-Oakland-Hayward, CA	0.6402	0.117092	0.740617	0.0737401
Phoenix-Mesa-Scottsdale, AZ	0.637541	0.0483282	0.814022	0.112352
Los Angeles-Long Beach-Anaheim, CA	0.623852	0.129184	0.779157	0.145685
Minneapolis-St. Paul-Bloomington, MN-WI	0.578898	0.144622	0.586778	0.0400663
Riverside-San Bernardino-Ontario, CA	0.54275	0.0548547	0.77159	0.0959834

Table 1: 2017 Commute Gap Statistics and $\mathbf{H}_{1500}$

Spatio-Temporal Dynamics

To measure spatiotemporal dynamics, we examine the temporal variance in measured segregation levels at each spatial scale, the results of which are shown in Figure 3, which plots the coefficient of variation for segregation measured at each spatial scale in each metropolitan region as a heatmap.[7]. The x-axis displays the bandwidth distance used to calculate the egohood-based $\tilde{H}$, and the cell for each metro at each distance is shaded by the value of the coefficient of variation (with darker colors indicating greater variation). The heatmaps give indication of how segregation *changes* at each spatial scale over time; if dark colors cluster to the left, then segregation is most variable at smaller scales, whereas the opposite is true for larger scales, and if segregation varies at all scales simultaneously, the bar will be relatively solid throughout.

Perhaps unsurprisingly, segregation levels over time are most variable at smaller spatial scales, but the trend is not universal for all metropolitan regions, neighborhoods versus laborhoods, or ethnic groups. The heatmaps further clarify the trends observed in Tables 2, 3 that residential segregation is typically the most variable at small scales—however, when metropolitan areas have significant absolute changes in segregation, it tends to occur at all scales. This is evident from metropolitan regions like Miami, Detroit, and New York, whose changes are relatively constant across scales. Furthermore, the most dynamic regions are not necessarily consistent across racial and ethnic groups. Miami is the most dynamic metropolitan region for Hispanics whereas for the black population Washington D.C. is the most dynamic at larger scales whereas Riverside is the most dynamic at small scales. Looking across the four heatmaps, several large-scale patterns are present. For residential locations, segregation typically changes at smaller scales more than larger ones for Black and Hispanic/Latino groups (i.e. the gradients tend to move left-to-right). For workplace locations, the opposite is typically true for both groups: segregation tends to change most at larger spatial scales (i.e. the gradients are reversed). Furthermore, distance seems to play a larger role in residential segregation, as the gradients in the top two figures are generally steeper than the bottom two figures, meaning that when workplace segregation changes, it typically does so across the board at all spatial scales, whereas when residential segregation changes, it usually does so in local pockets.

For residential segregation, change is not static or universal; places with some of the highest segregation levels, like Atlanta, Baltimore, and St. Louis have hardly any variation in segregation at *any* spatial scale, whereas other metros like Washington D.C., Riverside, and Boston have a great deal of variation in segregation, but heterogeneity with respect to scale, ethnic group, and workplace versus residential location. Finally, when segregation levels are changing in a given metropolitan region, the scales, locations, and groups for which they are do not necessarily coincide, for example Detroit shows hardly any variation in Black residential segregation at any scale, but a great deal of variation in Black workplace segregation at all scales. Elsewhere, like Washington D.C. Black segregation is changing for both home and workplace locations (at all scales) but Hispanic/Latino segregation varies little, and in Riverside neighborhood segregation is changing for both groups, but laborhood segregation remains unchanged.

Beyond these general patterns, several individual metropolitan regions warrant further discussion. Figures 4, 5, 6, 7 show segregation profiles for selected metropolitan regions (and plots for all

[7] For a tabular presentation of these statistics, see Table 4 and Table 5 in the Appendix

Figure 3: Heatmap of Temporal Variation in Segregation Across Spatial Scales

30 are available in the appendix). In these figures, the shape of each segregation profile describes the geographic scale of neighborhood and laborhood segregation in each MSA, with blue lines representing residential segregation and red lines representing workplace segregation. Lighter colors indicate earlier time periods and darker colors are more recent. Thus, the distance between the blue curves or the red curves describes the increase or decrease in segregation at different scales between consecutive years (for residential or workplace locations respectively). Meanwhile, the distance between the red and blue curves at the same temporal scale (denoted in the legend) describes the *daily* change in contextual segregation the population experiences over the course of a typical day.

Figure 4 shows the multiscalar profiles for neighborhoods and laborhoods measuring black/white and Hispanic/non-Hispanic segregation in the St. Louis metropolitan region. St Louis is notable for two reasons. First, it has some of the highest measured levels of black/white segregation at every scale, for both residential and workplace segregation. Second, workplace laborhood segregation for Hispanics is *greater* than residential neighborhood segregation, indicating that Hispanics in the St. Louis metropolitan region actually commute to segregation. From the perspective of labor and economic inequality, this finding is stark and suggests that Hispanics and non-Hispanics in the St. Louis region tend to work in categorically different labor markets whose industries and occupations are spatially distinct. A lurking variable in this equation may be differential levels of educational attainment or occupational training, which suggests that one way to reduce Hispanic segregation in St. Louis might be through economic development or increasing educational opportunities that expose residents from diverse ethnic backgrounds to a wider variety of employment opportunities.

The Detroit metropolitan region, shown in Figure 5, has some of the highest measured levels of black/white segregation at any scale, and it has one of the flattest segregation profiles (see Table 2), suggesting that the black and white populations in the region share vastly different environments. Despite these high levels, Detroit also shows among the greatest levels of variation in black/white segregation suggesting that the region may be undergoing some important changes. In general, the trend has been a (socially) positive one, with segregation levels decreasing over the 2010-2017 span, though the decrease has not been strictly monotonic. This is true of both residential neighborhoods and workplace laborhoods. The Miami metropolitan region in Figure 6 has high levels of black/white segregation but also has some of the highest measured levels of Hispanic segregation at every scale. Furthermore, Miami is relatively dynamic over the eight year period, particularly in Hispanic/Latino segregation which shows high variance over all scales. Perhaps more importantly, Hispanic/Latino segregation in the Miami region is undergoing a recent *increase* at all spatial scales, following a prior period of increasing integration. The Minneapolis-St.Paul metropolitan region in Figure 7 stands out for two different patterns; first, it has one of the steepest slopes for its black/white segregation profile, indicating that the majority of the segregation between those populations arises from small scale differences rather than large scale ones. Second, the region's Hispanic/Latino workplace segregation levels are higher than residential levels at moderate scales.

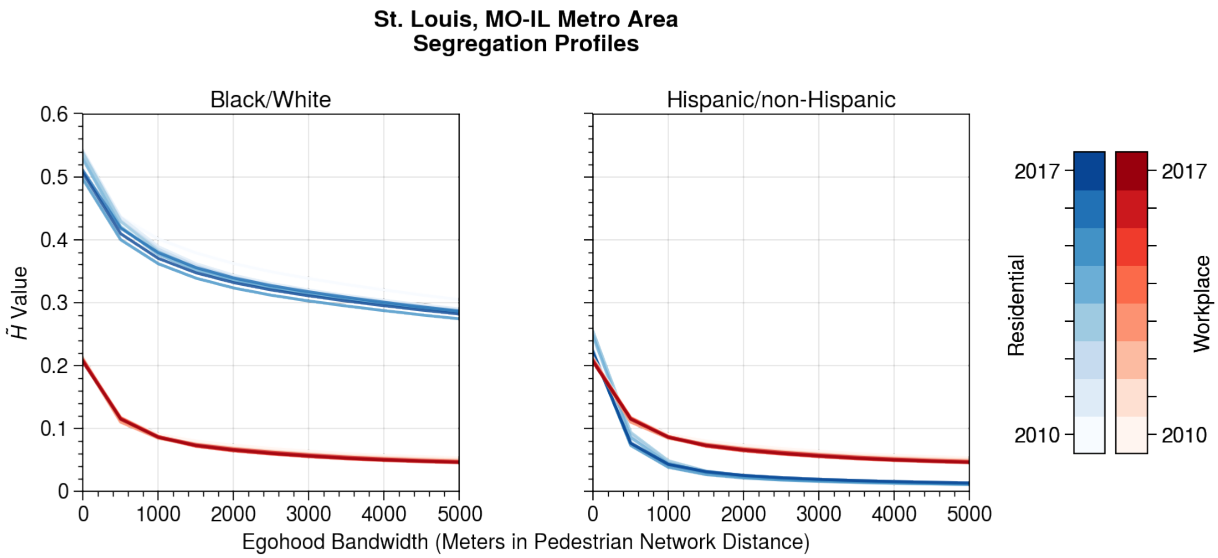


Figure 4: Residential & Workplace Segregation Profiles in the St. Louis Metro Region, 2010-2017

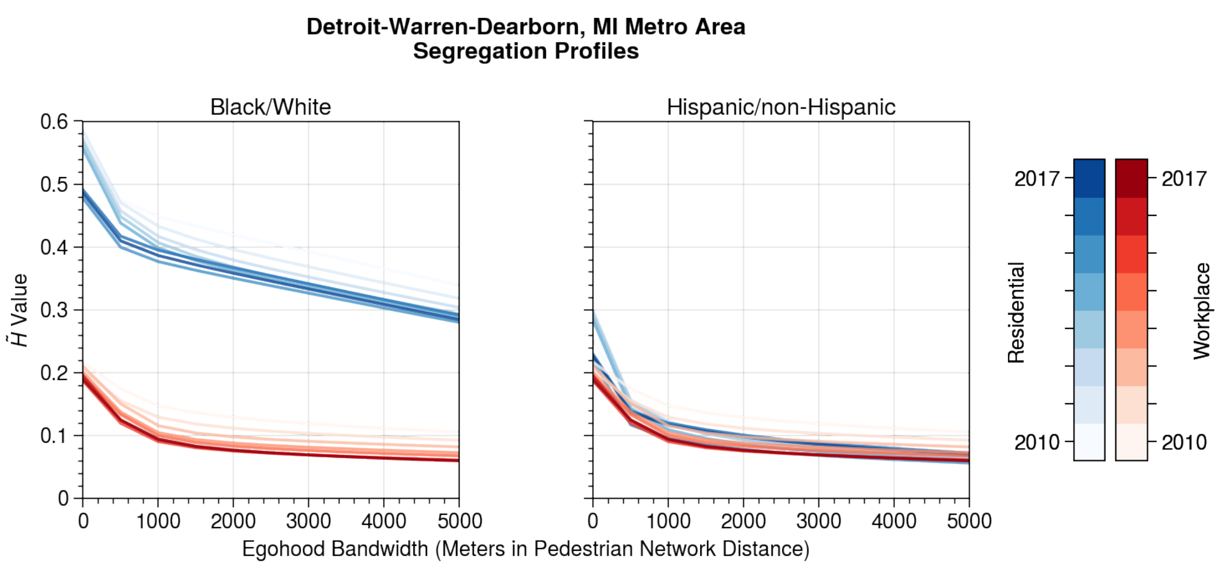


Figure 5: Residential & Workplace Segregation Profiles in the Detroit Metro Region, 2010-2017

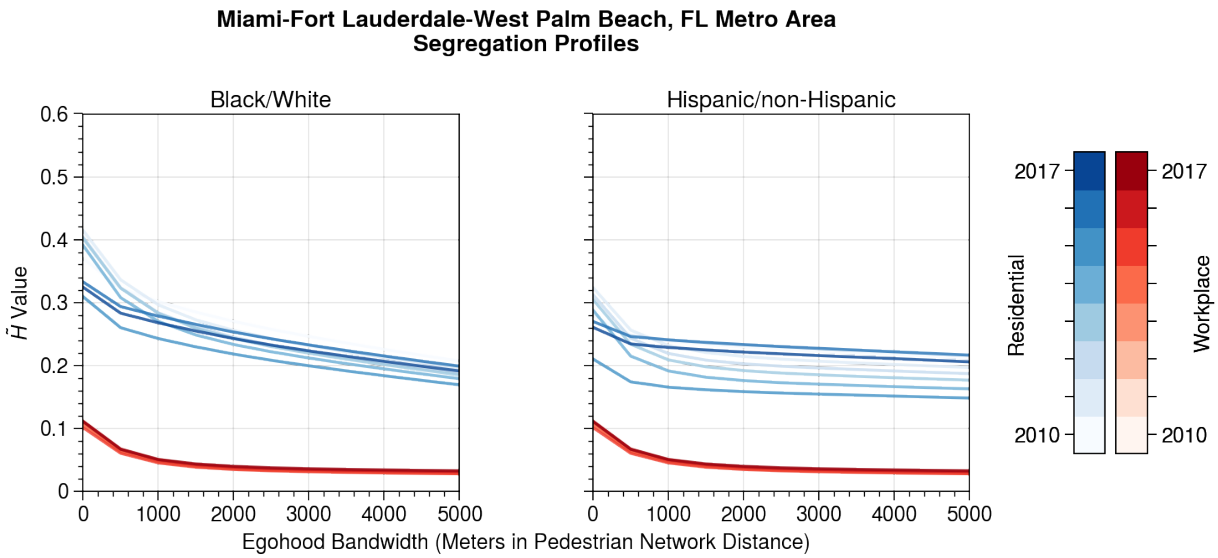


Figure 6: Residential & Workplace Segregation Profiles in the Miami Metro Region, 2010-2017

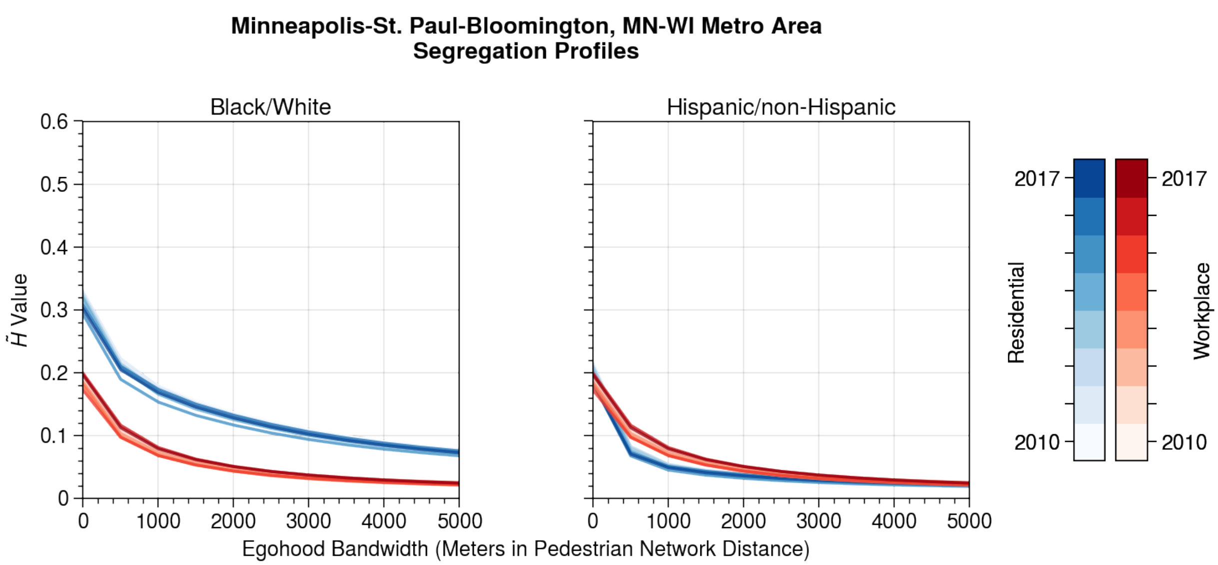


Figure 7: Residential & Workplace Segregation Profiles in the Minneapolis Metro Region, 2010-2017

DISCUSSION

A clear, if mildly surprising finding in this study is the exceedingly low level of daytime segregation in every one of the metropolitan areas we examined. Our work here confirms and expands those by Ellis et al. (2004) who found similar results in Los Angeles, and we show that they hold true for the rest of the country as well. While, in general, daytime segregation levels are low, another surprising finding we uncover is that in some metro areas, Hispanic/Latino segregation *increases* for workplace segregation than residential segregation. While residential segregation for Hispanic/Latino employees is generally much lower than for Black employees, the inverted positions of workplace and residential segregation curves for Hispanics/Latinos suggests possible labor market inequalities, and opens a doorway for additional research focused on these relationships. As a result, the daytime fluctuation in segregation is highest in metropolitan regions with the highest levels of residential (nighttime) segregation. From a public policy perspective, this finding has important implications for metropolitan housing and transportation policies, but it also suggests ramifications for other critical institutions such as education or healthcare services. The extremely low levels of daytime segregation observed across metropolitan regions in this study make demonstrably clear that cities are dynamic, multiracial, multiethnic spaces during the daytime, in which people from all origins share the same local environments. When they commute home, however, residents in many metropolitan regions return to highly segregated environments whose local institutions, resources, political representation, etc. all follow a racialized spatial order.

Since other critical services such as education are structured according to residential addresses, this means that while parents commute to highly integrated environments, their children likely attend highly segregated schools, places of worship, healthcare services, and retail shopping services. From the perspective of intergenerational racial equality, these patterns mean that residential environments artificially insulate social groups from another during their formative years, helping isolate racial and ethnic groups into daytime environments fundamentally different from those they will experience as adults. More simply, these findings suggest that children are placed into institutions that highly racially segregated, and which may be improperly training them for the highly integrated environments they will experience once they join the workforce. Unfortunately, temporal dynamics from the *annual* scale suggest that these patterns are changing little over time. For most metropolitan regions there is little annual variance in segregation, and for most regions, segregation levels have moved in both directions.

Further, our "counterfactual" of sorts for our commute-gap statistic–that if every person in the region worked from home, the metric would be zero–displays the importance of understanding daily segregation dynamics and measuring the difference between residential and workplace activity spaces. As the COVID-19 pandemic begins to wind down, many lasting impacts on the economy, including the proliferation of teleworking and flexible scheduling means many employees may spend an increasing amount of time in highly segregated residential spaces that was once spent in highly integrated workplace environments. If workplace environments provide a small locus of interpersonal and intercultural exposure and exchange, then these trends could have profound consequences in the age of increasing political polarization and political violence.

In gentrifying metros, we might expect to see some level of temporal variation in segregation, as new residents move in and others, possibly, are displaced. We do not see an obvious pattern of this ilk in some of the most obvious gentrification hotspots like San Francisco, New York, or Chicago. One reason for this could be that while gentrification is a painful process for neighborhood residents, it remains a relatively acute harm, that generates racial and income mixing in only a small handful of neighborhoods, thus rendering the phenomenon undetectable using regional-level segregation statistics. Conversely, the "back to the city" movement articulated by Ehrenhalt (2012) a decade ago combined with the longstanding urban planning goal of greater jobs/housing balance in urban areas could provide a path toward several progressive goals simultaneously. Increasing urban dwelling through policy measures like infill development, affordable housing investments and transit density bonuses would meet many urban planning environmental goals by shortening commutes and reducing emissions, but our results suggest that such measures would also promote "social sustainability," by reducing the commute gap statistic, bringing racial and ethnic groups closer to their job locations and, necessarily, reducing residential segregation levels.

CONCLUSION

In this paper we perform a large-scale analysis of spatiotemporal segregation dynamics in large American metropolitan regions using data with both high temporal and spatial resolution. Using transport network analysis, we generate realistic measures of segregation at multiple scales, accounting for the unique geometry and contiguity patterns inherent in each metro's pedestrian travel networks. These measures capture the racial mix a person is likely to encounter in a typical pedestrian-scale "egohood" that radiates outward from their home or workplace location. Taking full advantage of the workplace and residential tabulations in the Census LODES data, we provide unique insight into the ways that racial and ethnic segregation fluctuate over the course of a typical weekday, and the spatial scales at which they do so. By repeating this process for each year of available data, our results also yield information about the *annual* fluctuation in segregation levels for both daytime and nighttime at every spatial scale.

Our results reveal the deep complexity with which segregation is experienced over the course of the day, and the spatial scales over which segregation is changing for both Black Americans and Hispanic/Latino Americans. More specifically, our results show that most metropolitan regions have highly integrated laborhoods—that is, at the daily scale, we find workplace (and, by extension, metro areas at large) segregation levels are very low in absolute terms for every one of the regions we studied, although in some regions Hispanic/Latino segregation is greater in laborhoods than in neighborhoods at some spatial scales. At an annual scale, most regions show a general trend in decreasing residential segregation over time, particularly at small spatial scales, though the trend is neither universal not monotonic so we hesitate to draw conclusions regarding an overall trend toward segregation reduction. Furthermore, these data pertain to the period immediately proceeding the COVID-19 pandemic that has shifted both workplace location dynamics and the residential housing market, two trends whose ultimate impacts are yet unknown. When the data become available, we plan to examine these questions in detail.

From a methodological perspective, we argue that this analysis extends the current state of the science for providing a comprehensive picture of urban segregation accounting for multiple spatial and temporal scales simultaneously. Incorporating network analysis into the computation of each segregation statistic injects behaviorial realisim as well as local nuance into the measurement strategy, as man-made features like non-gridded street patterns, railroad tracks, and dead-ends that serve to partition the urban environment and inhibit social interaction across spaces are implicit in the analysis. Further, using administrative data rather than activity-based data mean we can scale the analysis to provide evidence across a wide range of metropolitan areas and incorporate measurements for each year, rather than a single cross-section. Although LODES data are atypical in demographic work, they provide unique insight in this case into both the daily and annual variation in racial and ethnic segregation each metropolitan region experiences. Further, because these data are available at high resolutions, both spatial and temporal, they offer a sound, cost-effective, and nationally-scalable alternative to more expensive and personally invasive personal mobility studies that rely on GPS and/or cell phone data.

When used for understanding metropolitan segregation patterns, LODES data do have drawbacks compared with activity-tracking data. First, LODES data contain information solely on the residential and workplace locations of workers, meaning we cannot observe segregation levels for populations other than those employed. Second, because there are only two tabulation times (i.e. residential/nighttime and workplace/daytime) we lack important information about the time and locations of different commuting patterns, which themsevelves may be subjected to unique segregation levels (Wang et al., 2018). Finally, the collection and reporting of LODES data can be subject to idiosyncratic decisions that can influence our interpretation regarding the location of employees during the workday. For example, in some locations postal employment is reported at local post offices (e.g. mailmen and mailwomen are reported to work at the location from which their route begins) and in other cases it is reported at a single post office. In other similar cases, it is possible, for example for a university to report its entire academic employment at a single campus address, rather than allocating professors to their office or classroom locations. In general, we believe these issues are not widespread and are unlikely to severely bias our results, even when present. Nevertheless it remains important to qualify and verify our findings relative to other administrative and activity tracking data, and we look forward to collaborating with other researchers to expand our findings in this regard.

REFERENCES

Boeing, G. (2018). A multi-scale analysis of 27,000 urban street networks: Every US city, town, urbanized area, and Zillow neighborhood. *Environment and Planning B: Urban Analytics and City Science*, 239980831878459. https://doi.org/10.1177/2399808318784595

Catney, G. (2018). The complex geographies of ethnic residential segregation: Using spatial and local measures to explore scale-dependency and spatial relationships. *Transactions of the Institute of British Geographers*, *43*(1), 137–152. https://doi.org/10.1111/tran.12209

Charles, C. Z. (2003). The Dynamics of Racial Residential Segregation. *Annual Review of Sociology*, *29*(1), 167–207. https://doi.org/10.1146/annurev.soc.29.010202.100002

contributors, O. (2017). *Planet dump retrieved from https://planet.osm.org*. https://www.openstreetmap.org. https://www.openstreetmap.org

Cortes, R. X., Knaap, E., Rey, S., Kang, W., Stephens, P., Wolf, L. J., Härkönen, A., Gaboardi, J., & Arribas-

Bel, D. (2019). *pysal/segregation: Release 1.1.1 (bug fixes)*. https://doi.org/10.5281/ZENODO.3343074

Cortes, R. X., Rey, S., Knaap, E., & Wolf, L. J. (2019). An open-source framework for non-spatial and spatial segregation measures: the PySAL segregation module. *Journal of Computational Social Science*. https://doi.org/10.1007/s42001-019-00059-3

Dannemann, T., Sotomayor-Gómez, B., & Samaniego, H. (2018). The time geography of segregation during working hours. *Royal Society Open Science*, *5*(10), 180749. https://doi.org/10.1098/rsos.180749

Ehrenhalt, A. (2012). *The great inversion and the future of the {American} city*. Random House.

Ellis, M., Wright, R., & Parks, V. (2004). Work Together, Live Apart? Geographies of Racial and Ethnic Segregation at Home and at Work. *Annals of the Association of American Geographers*, *94*(3), 620–637. https://doi.org/10.1111/j.1467-8306.2004.00417.x

Foti, F., Waddell, P., & Luxen, D. (2012). A Generalized Computational Framework for Accessibility : From the Pedestrian to the Metropolitan Scale. *4th Transportation Research Board Conference on Innovations in Travel Modeling (ITM)*, 1–14. http://onlinepubs.trb.org/onlinepubs/conferences/2012/4thITM/Papers-A/0117-000062.pdf

Fowler, C. S. (2016). Segregation as a multiscalar phenomenon and its implications for neighborhood-scale research: the case of South Seattle 1990–2010. *Urban Geography*, *37*(1), 1–25. https://doi.org/10.1080/02723638.2015.1043775

Hansen, W. G. (1959). How Accessibility Shapes Land Use. *Journal of the American Institute of Planners*, *25*(2), 73–76. https://doi.org/10.1080/01944365908978307

Hipp, J. R., Faris, R. W., & Boessen, A. (2012). Measuring 'neighborhood': Constructing network neighborhoods. *Social Networks*, *34*(1), 128–140. https://doi.org/10.1016/j.socnet.2011.05.002

Kane, K., Hsu, J., Cryer, J., & Anderson, M. (2020). Affecting commute mode choice in Southern California: Which employer-based strategies work? *Journal of Transport and Land Use*, *13*(1), 255–272. https://doi.org/10.5198/jtlu.2020.1558

Kim, Y.-A., & Hipp, J. R. (2019). *Street Egohood: An Alternative Perspective of Measuring Neighborhood and Spatial Patterns of Crime*. Springer US. https://doi.org/10.1007/s10940-019-09410-3

Knaap, E., Kang, W., Rey, S., Wolf, L. J., Cortes, R. X., & Han, S. (2019). *geosnap: The Geospatial Neighborhood Analysis Package*. https://doi.org/10.5281/ZENODO.3526163

Kwan, M.-P. (2015). Beyond Space (As We Knew It): Toward Temporally Integrated Geographies of Segregation, Health, and Accessibility. In *Space-time integration in geography and GIScience* (Vol. 5608, pp. 39–51). Springer Netherlands. https://doi.org/10.1007/978-94-017-9205-9_4

Le Roux, G., Vallée, J., & Commenges, H. (2017). Social segregation around the clock in the Paris region (France). *Journal of Transport Geography*, *59*, 134–145. https://doi.org/10.1016/j.jtrangeo.2017.02.003

Lee, B. A., Reardon, S. F., Firebaugh, G., Farrell, C. R., Matthews, S. A., & O'Sullivan, D. (2008). Beyond the Census Tract: Patterns and Determinants of Racial Segregation at Multiple Geographic Scales. *American Sociological Review*, *73*(5), 766–791. https://doi.org/10.1177/000312240807300504

Lee, K. O. (2017). Temporal dynamics of racial segregation in the United States: An analysis of household residential mobility. *Journal of Urban Affairs*, *39*(1), 40–67. https://doi.org/10.1111/juaf.12293

Levinson, D. M. (1998). Accessibility and the journey to work. *Journal of Transport Geography*, *6*(1), 11–21. https://doi.org/10.1016/S0966-6923(97)00036-7

Madden, J. F., & Ruther, M. (2018). The paradox of expanding ghettos and declining racial segregation in large U.S. metropolitan areas, 1970–2010. *Journal of Housing Economics*, *40*(January), 117–128. https://doi.org/10.1016/j.jhe.2018.01.003

Massey, D. S. (1978). On the {Measurement} of {Segregation} as a {Random} {Variable}. *American Sociological Review*, *43*(4), 587–590.

Massey, D. S. (2020). Still the Linchpin: Segregation and Stratification in the USA. *Race and Social Problems*, *12*(1), 1–12. https://doi.org/10.1007/s12552-019-09280-1

Massey, D. S., & Hajnal, Z. L. (1995). The Changing Geographic Structure of Black-White Segregation in the United States. *Social Science Quarterly*, *76*(3), 527–542. http://www.jstor.org/stable/44072648

Östh, J., Clark, W. A. V., & Malmberg, B. (2015). Measuring the Scale of Segregation Using k -Nearest Neighbor Aggregates. *Geographical Analysis*, *47*(1), 34–49. https://doi.org/10.1111/gean.12053

Park, Y. M., & Kwan, M. (2018). Beyond residential segregation: A spatiotemporal approach to examining multi-contextual segregation. *Computers, Environment and Urban Systems*, *May*, 1–11. https://doi.org/10.1016/j.compenvurbsys.2018.05.001

Reardon, S. F., Farrell, C. R., Matthews, S. A., O'Sullivan, D., Bischoff, K., & Firebaugh, G. (2009). Race and space in the 1990s: Changes in the geographic scale of racial residential segregation, 1990–2000. *Social Science Research*, *38*(1), 55–70. https://doi.org/10.1016/j.ssresearch.2008.10.002

Reardon, S. F., & Firebaugh, G. (2002). Measures of multigroup segregation. In R. M. Stolzenberg (Ed.), *Sociological {methodology}* (Vol. 32, pp. 33–67). Blackwell Publishing. https://doi.org/10.1111/1467-9531.00110

Reardon, S. F., Matthews, S. A., O'Sullivan, D., Lee, B. A., Firebaugh, G., Farrell, C. R., & Bischoff, K. (2008). The Geographic Scale of Metropolitan Racial Segregation. *Demography*, *45*(3), 489–514. https://doi.org/10.1353/dem.0.0019

Reardon, S. F., & O'Sullivan, D. (2004). Measures of spatial segregation. *Sociological Methodology*, *34*(1), 121–162. https://doi.org/10.1111/j.0081-1750.2004.00150.x

Rey, S. J., & Anselin, L. (2010). PySAL: A Python Library of Spatial Analytical Methods. In *Handbook of applied spatial analysis* (Vol. 37, pp. 175–193). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-03647-7_11

Roberto, E. (2018). The Spatial Proximity and Connectivity Method for Measuring and Analyzing Residential Segregation. *Sociological Methodology*, *48*(1), 008117501879687. https://doi.org/10.1177/0081175018796871

Sampson, R. J., & Levy, B. L. (2020). Beyond Residential Segregation: Mobility-Based Connectedness and Rates of Violence in Large Cities. *Race and Social Problems*, *12*(1), 77–86. https://doi.org/10.1007/s12552-019-09273-0

Tammaru, T., Strömgren, M., Ham, M. van, & Danzer, A. M. (2016). Relations between residential and workplace segregation among newly arrived immigrant men and women. *Cities*, *59*, 131–138. https://doi.org/10.1016/j.cities.2016.02.004

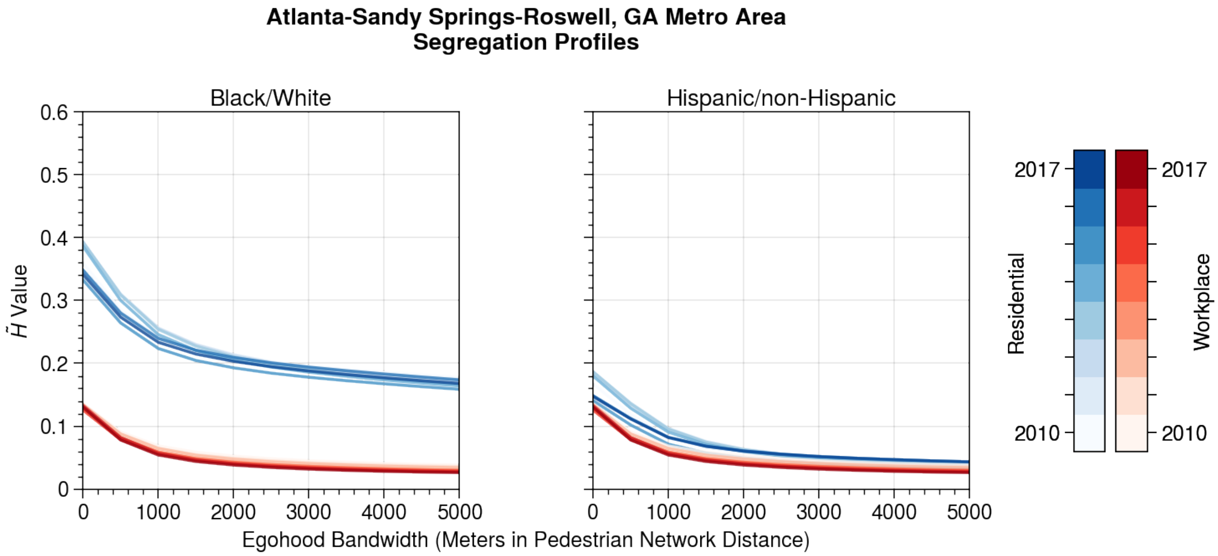
U.S. Census Bureau. (2020). *LEHD Origin-Destination Employment Statistics Data (2002-2017)*. U.S. Census Bureau. https://lehd.ces.census.gov/data

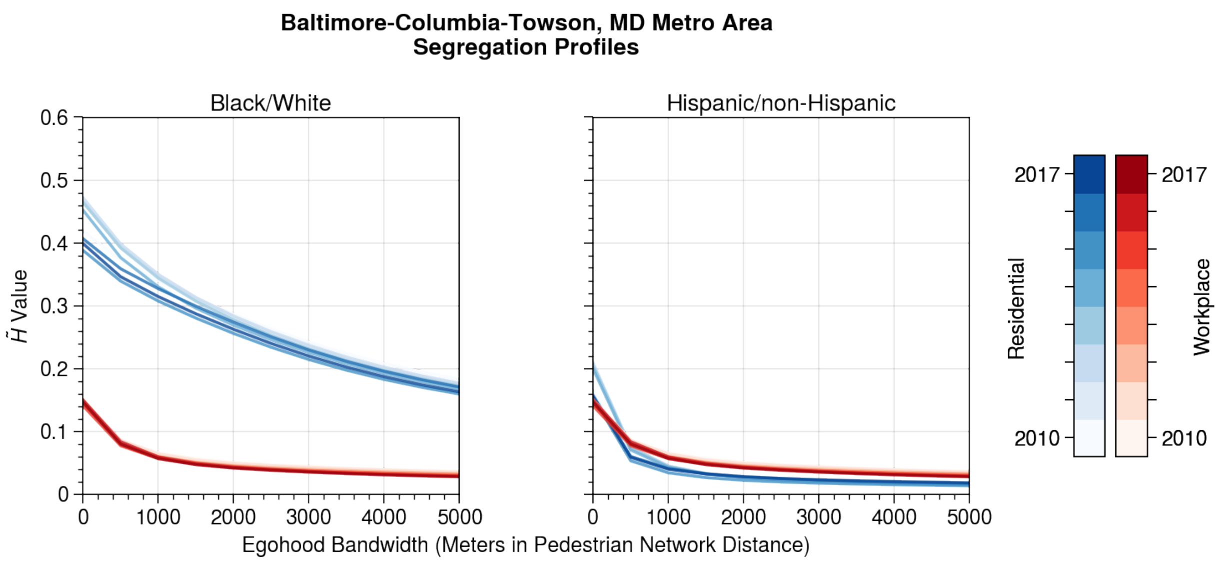
Wang, Q. (2010). How Does Geography Matter in the Ethnic Labor Market Segmentation Process? A Case Study of Chinese Immigrants in the San Francisco CMSA. *Annals of the Association of American Geographers*, *100*(1), 182–201. https://doi.org/10.1080/00045600903379083

Wang, Q., Phillips, N. E., Small, M. L., & Sampson, R. J. (2018). Urban mobility and neighborhood isolation in America's 50 largest cities. *Proceedings of the National Academy of Sciences*, *115*(30), 7735–7740. https://doi.org/10.1073/pnas.1802537115

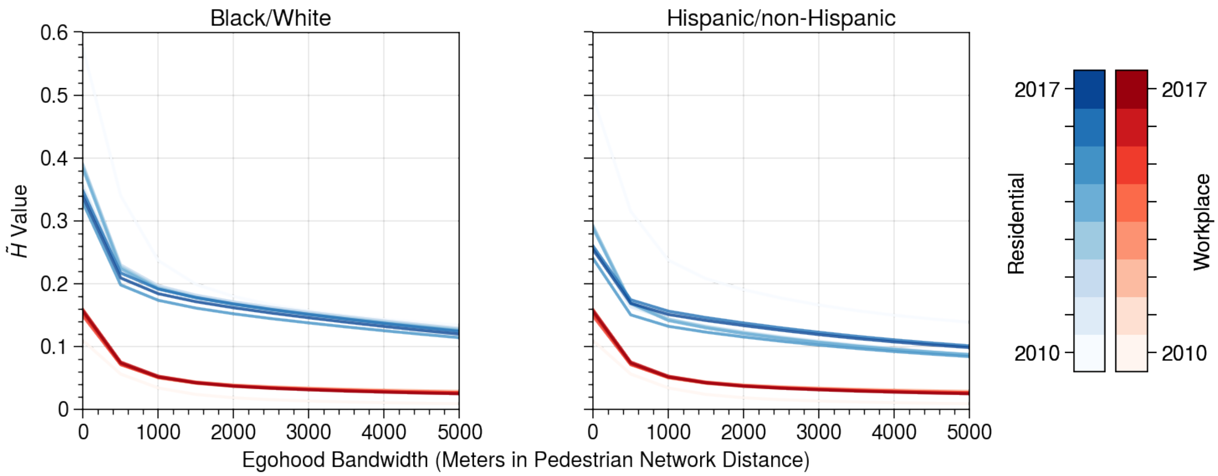
Zhang, X., Wang, J., Kwan, M.-P., & Chai, Y. (2018). Reside nearby, behave apart? Activity-space-based segregation among residents of various types of housing in Beijing, China. *Cities*, *July*, 1–15. https://doi.org/10.1016/j.cities.2018.10.009

APPENDIX

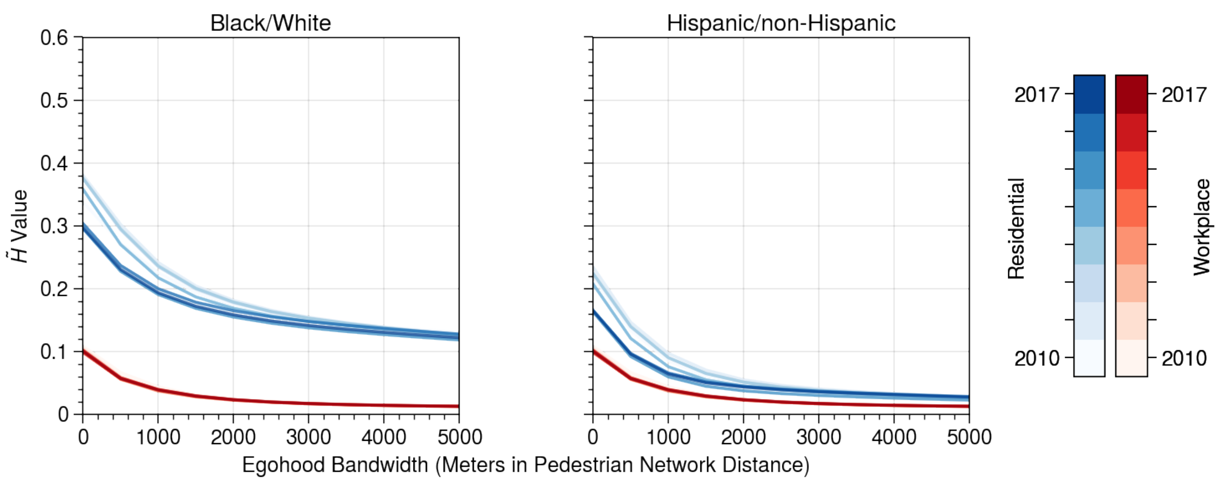

Atlanta-Sandy Springs-Roswell, GA Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
Residential
Workplace
2017
2010


Baltimore-Columbia-Towson, MD Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
Residential
Workplace
2017
2010

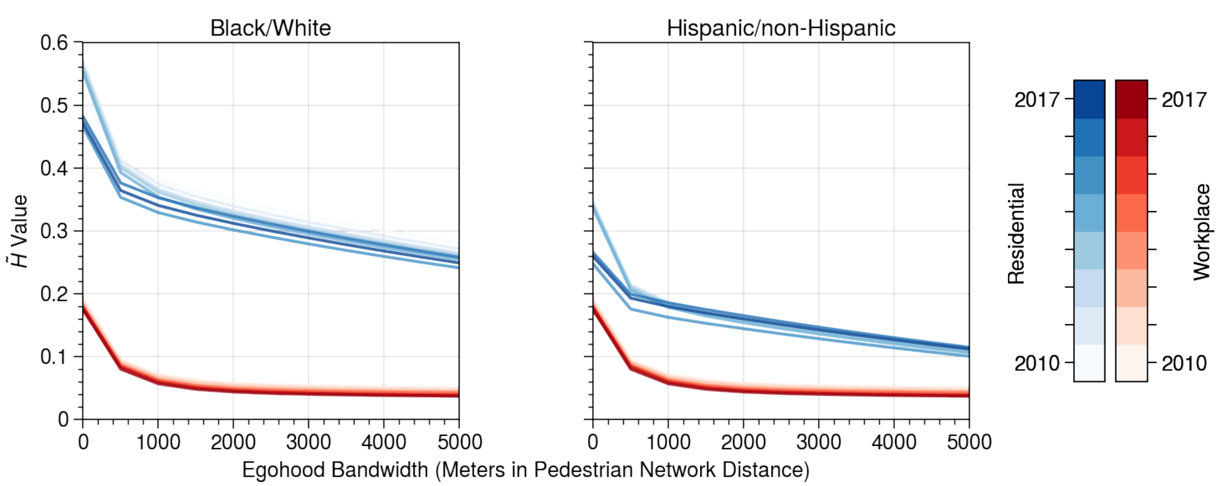
Boston-Cambridge-Newton, MA-NH Metro Area
Segregation Profiles

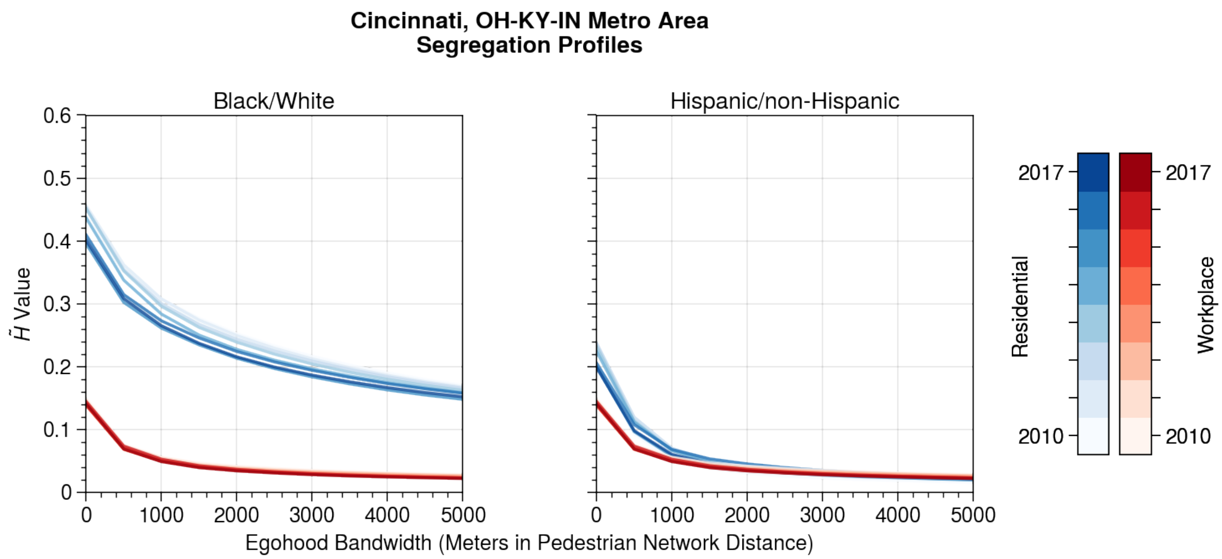


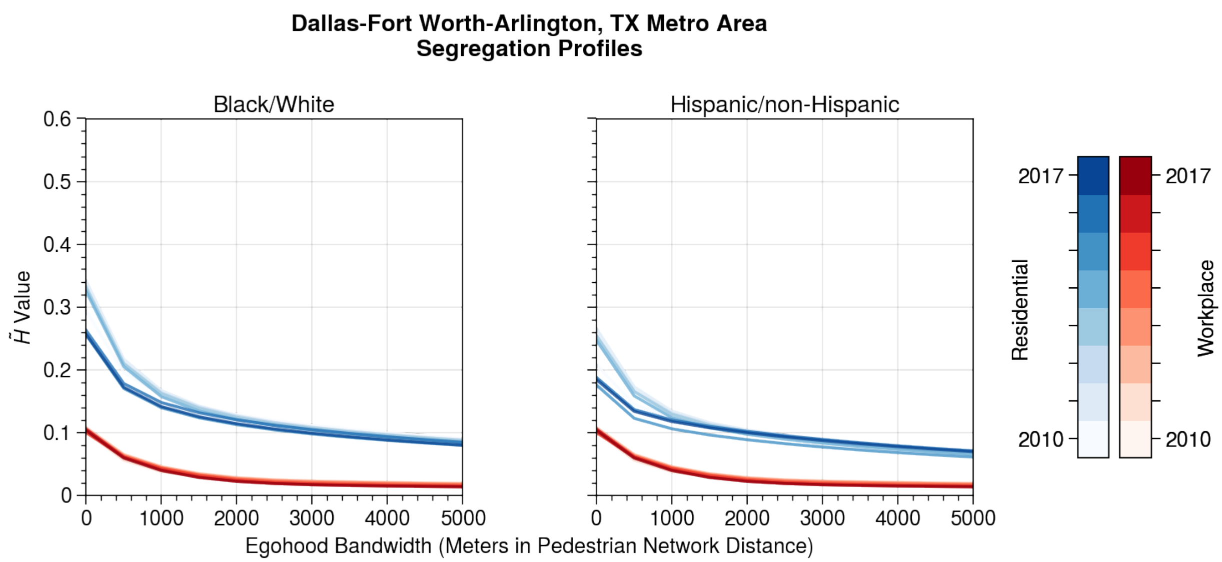
Charlotte-Concord-Gastonia, NC-SC Metro Area
Segregation Profiles

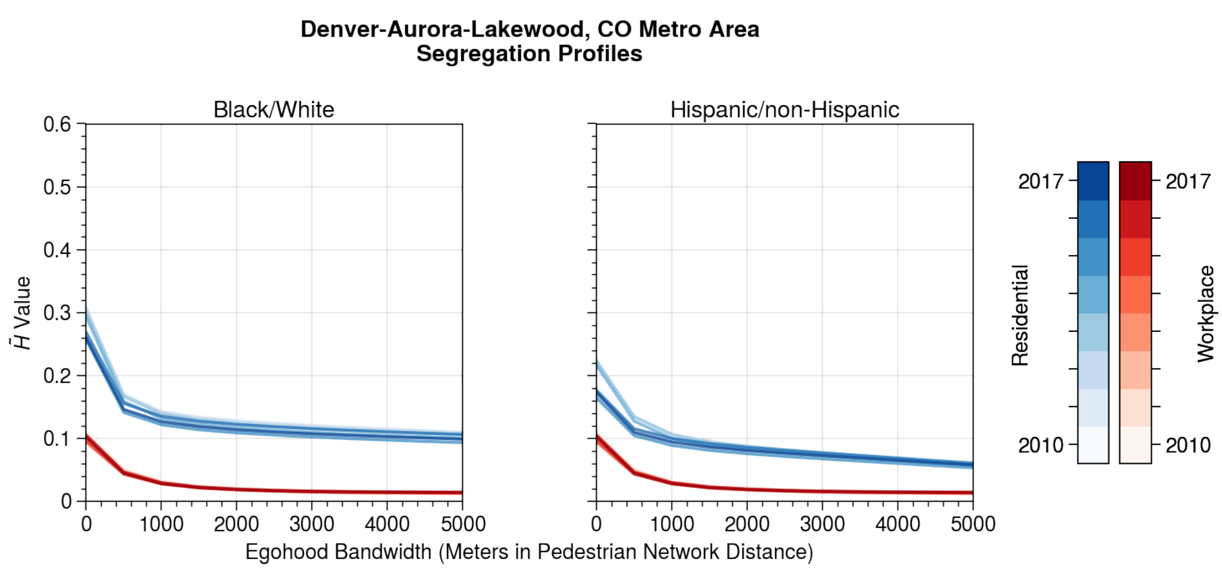


Chicago-Naperville-Elgin, IL-IN-WI Metro Area
Segregation Profiles

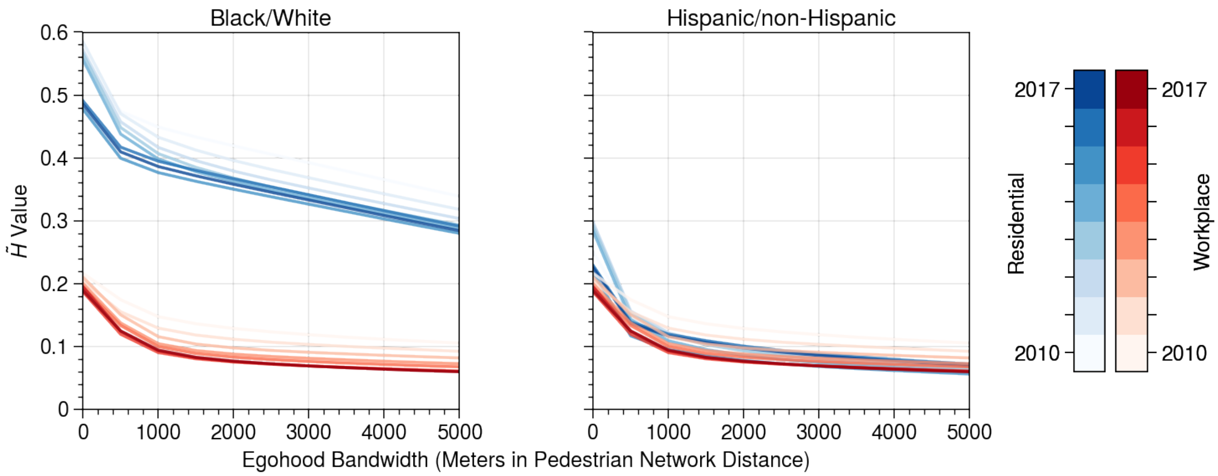



Cincinnati, OH-KY-IN Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
2017
2010
Residential
Workplace

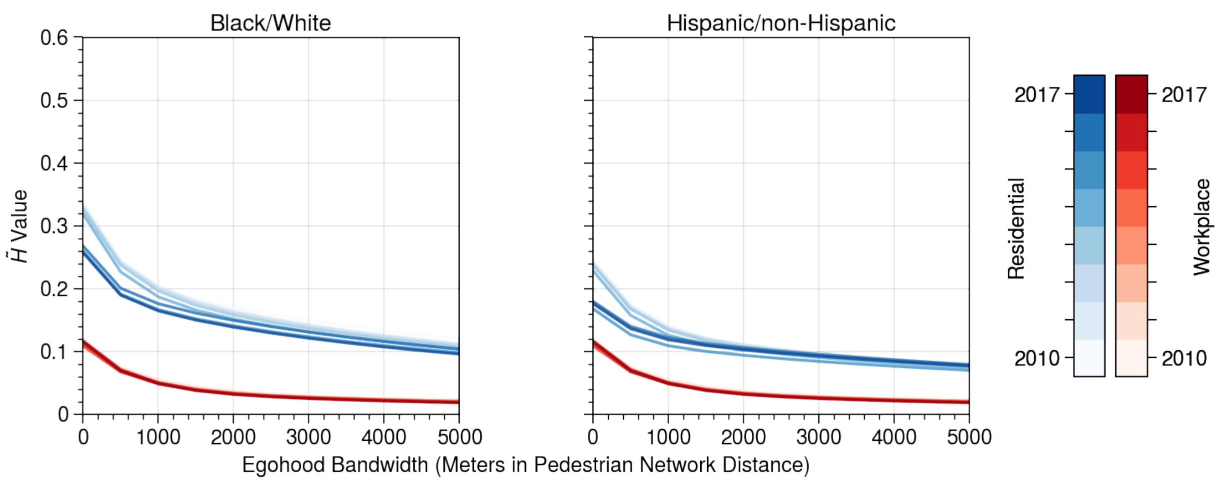

Dallas-Fort Worth-Arlington, TX Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
2017
2010
Residential
Workplace


Denver-Aurora-Lakewood, CO Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
2017
2010
Residential
Workplace

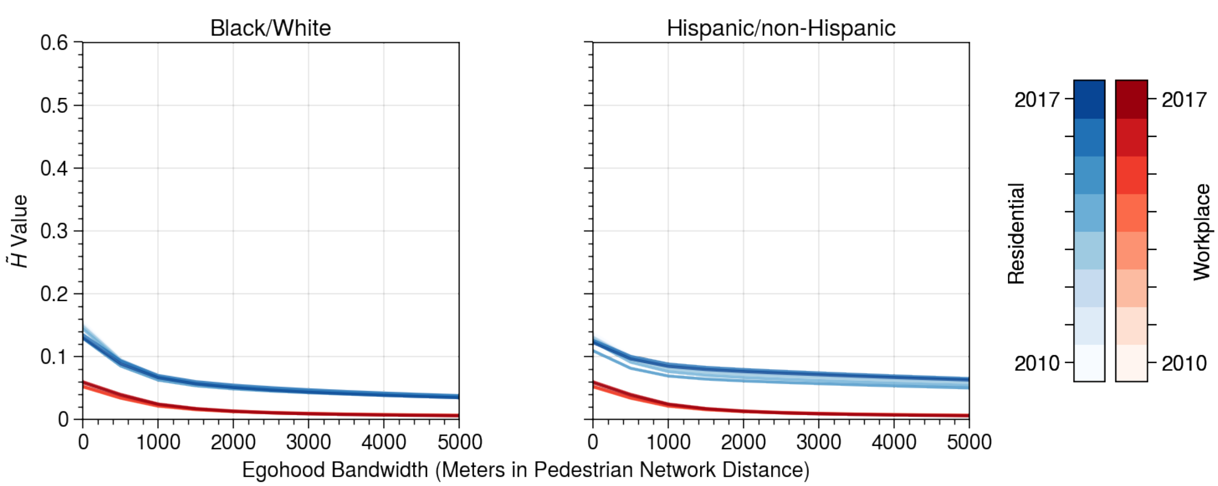
Detroit-Warren-Dearborn, MI Metro Area
Segregation Profiles



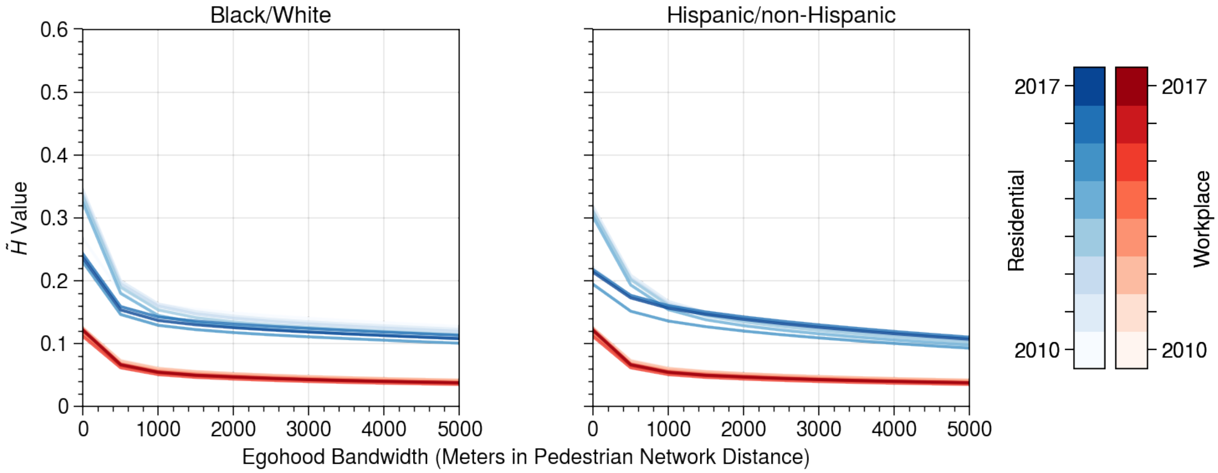
Houston-The Woodlands-Sugar Land, TX Metro Area
Segregation Profiles



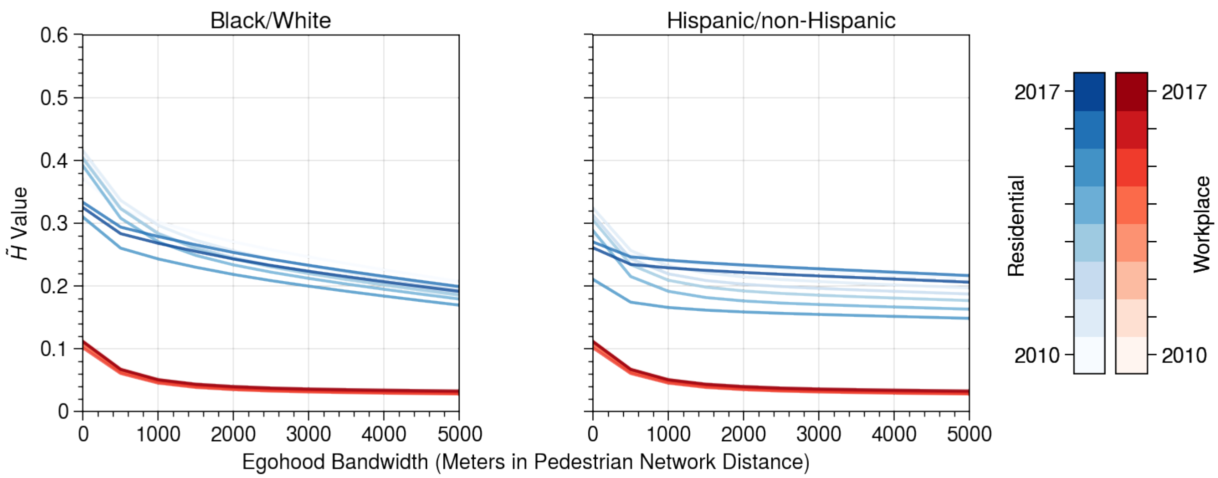
Las Vegas-Henderson-Paradise, NV Metro Area
Segregation Profiles



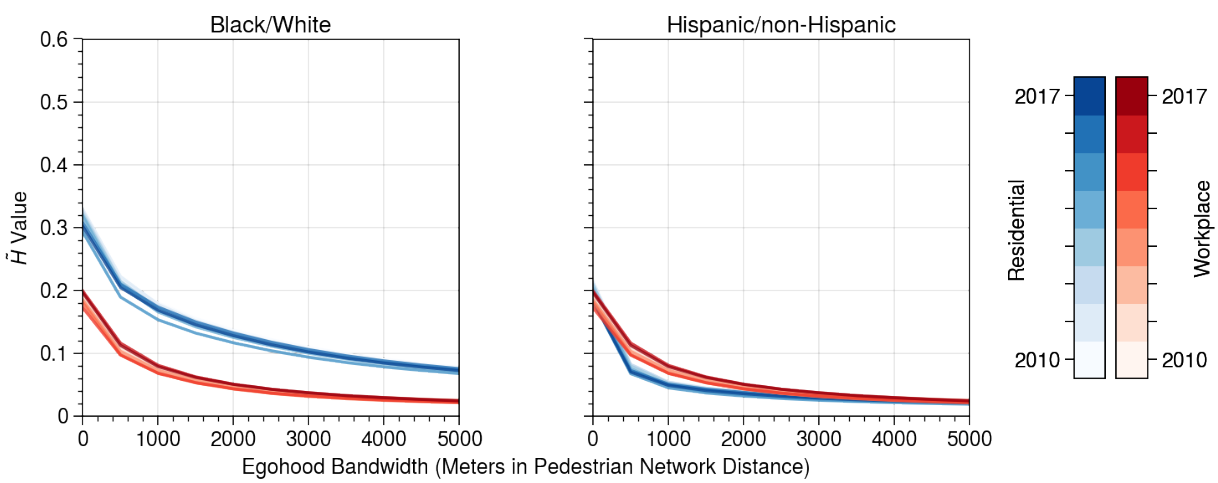
Los Angeles-Long Beach-Anaheim, CA Metro Area
Segregation Profiles



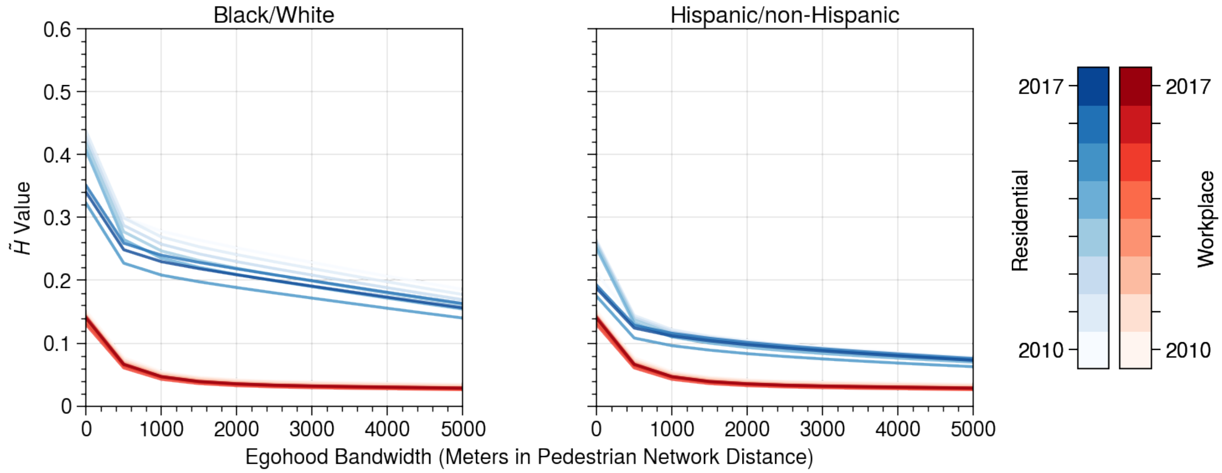
Miami-Fort Lauderdale-West Palm Beach, FL Metro Area
Segregation Profiles



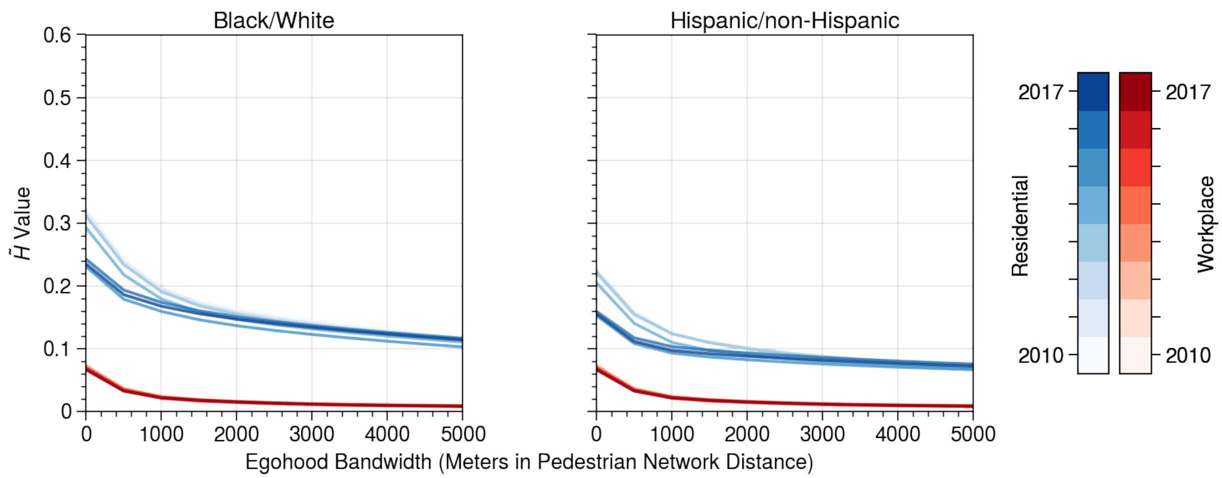
Minneapolis-St. Paul-Bloomington, MN-WI Metro Area
Segregation Profiles



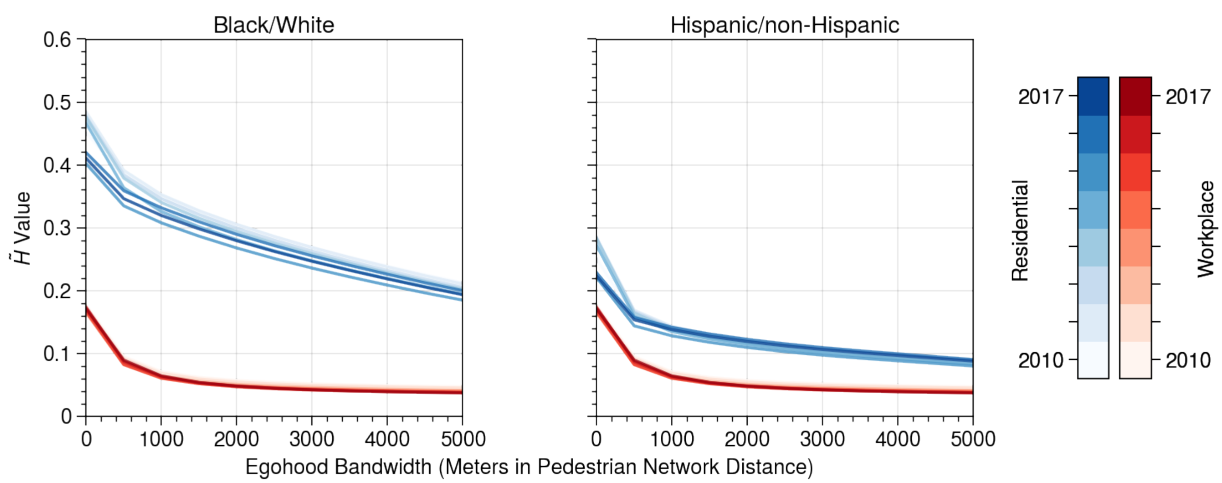
New York-Newark-Jersey City, NY-NJ-PA Metro Area
Segregation Profiles

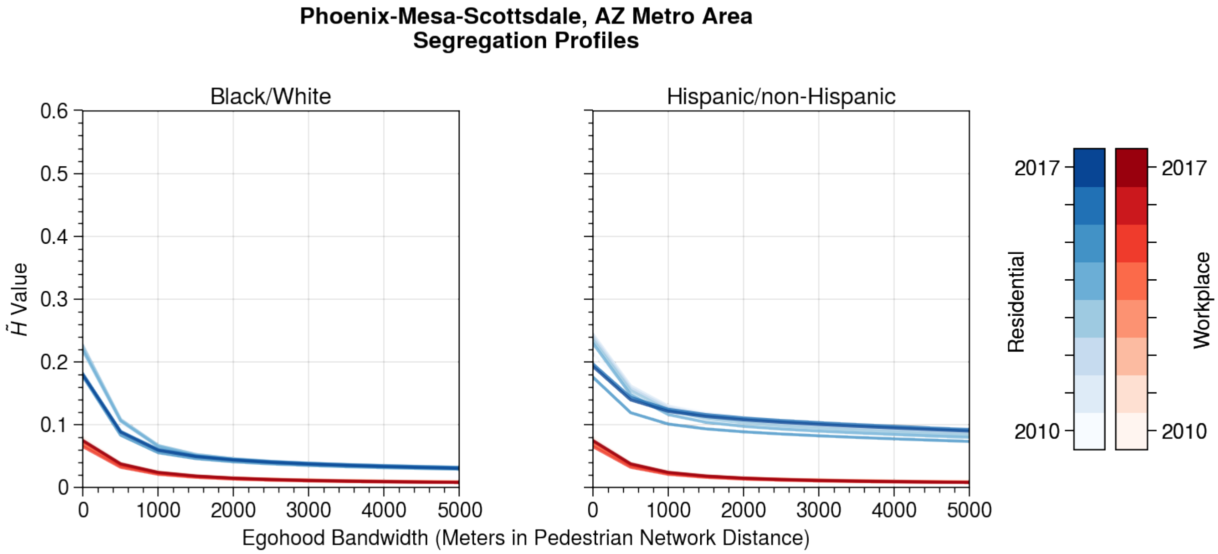


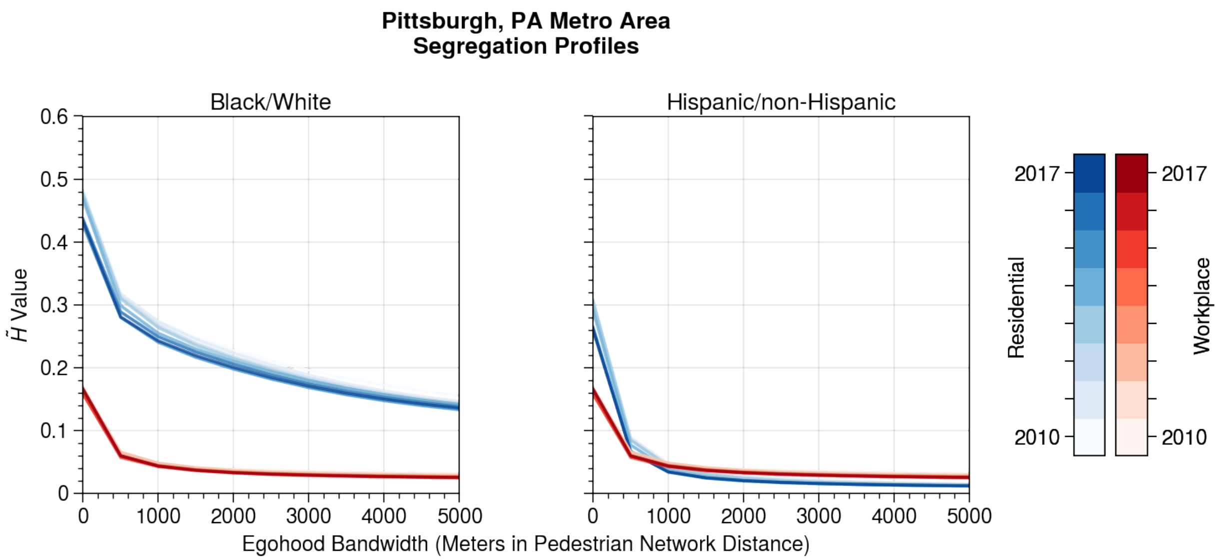
Orlando-Kissimmee-Sanford, FL Metro Area
Segregation Profiles

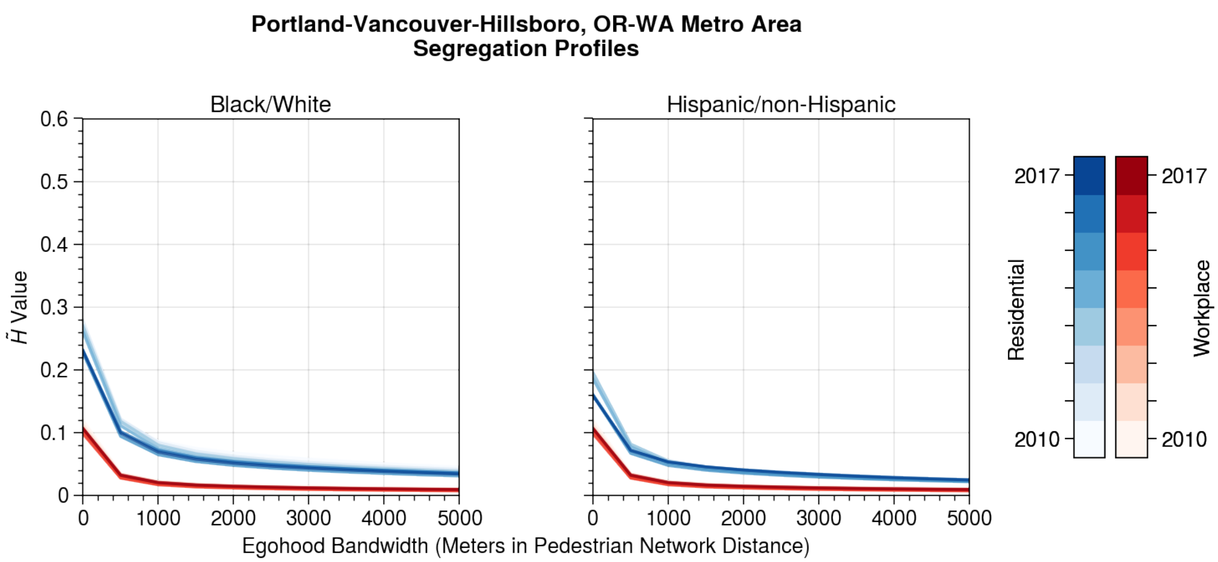


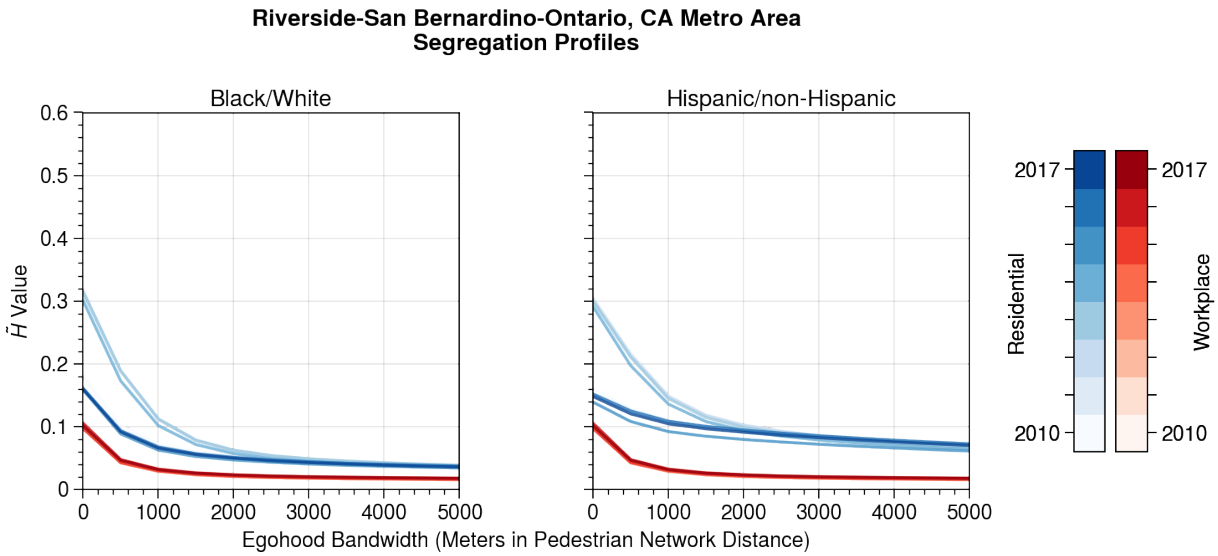
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area
Segregation Profiles

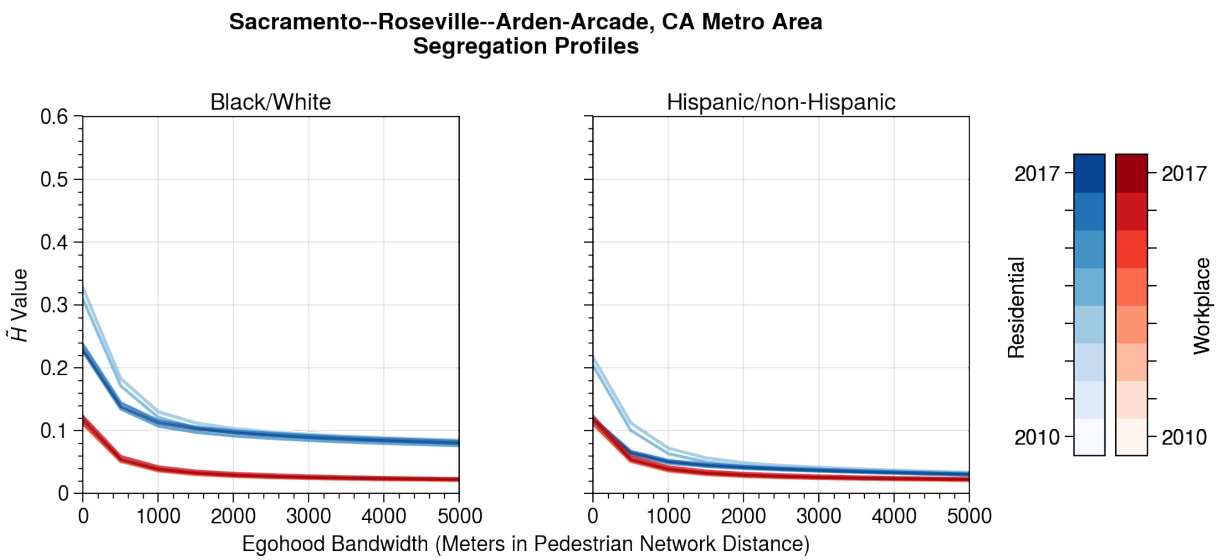


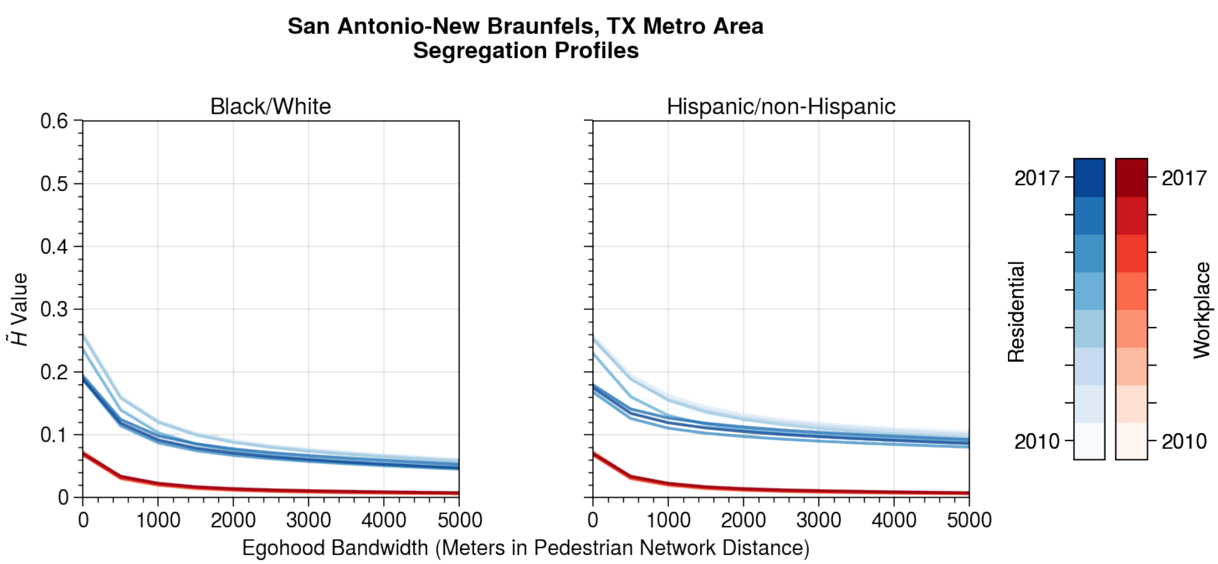

Phoenix-Mesa-Scottsdale, AZ Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
Egohood Bandwidth (Meters in Pedestrian Network Distance)
Residential
Workplace
2017
2010


Pittsburgh, PA Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
Egohood Bandwidth (Meters in Pedestrian Network Distance)
Residential
Workplace
2017
2010

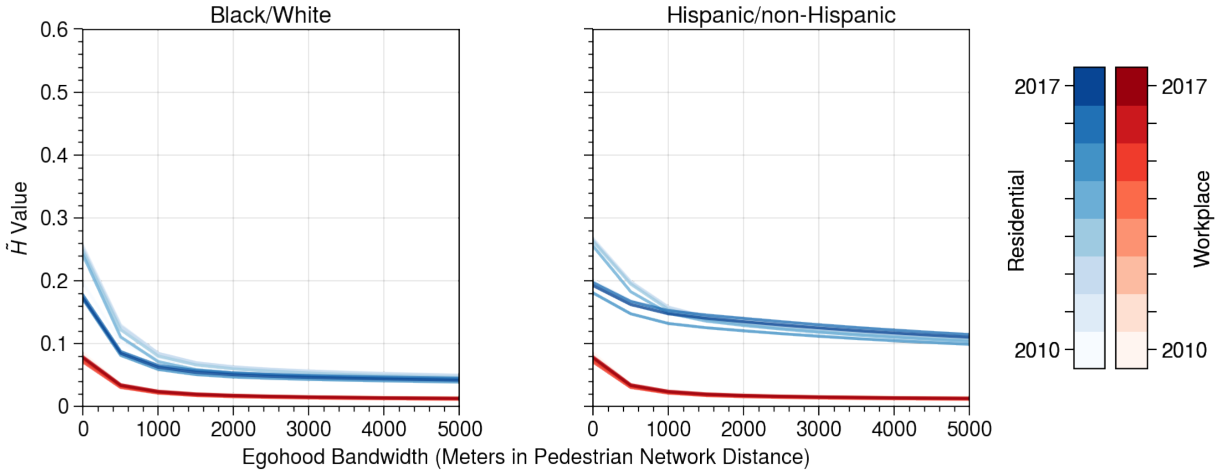

Portland-Vancouver-Hillsboro, OR-WA Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
Egohood Bandwidth (Meters in Pedestrian Network Distance)
Residential
Workplace
2017
2010


Riverside-San Bernardino-Ontario, CA Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
2017
2010
Residential
Workplace

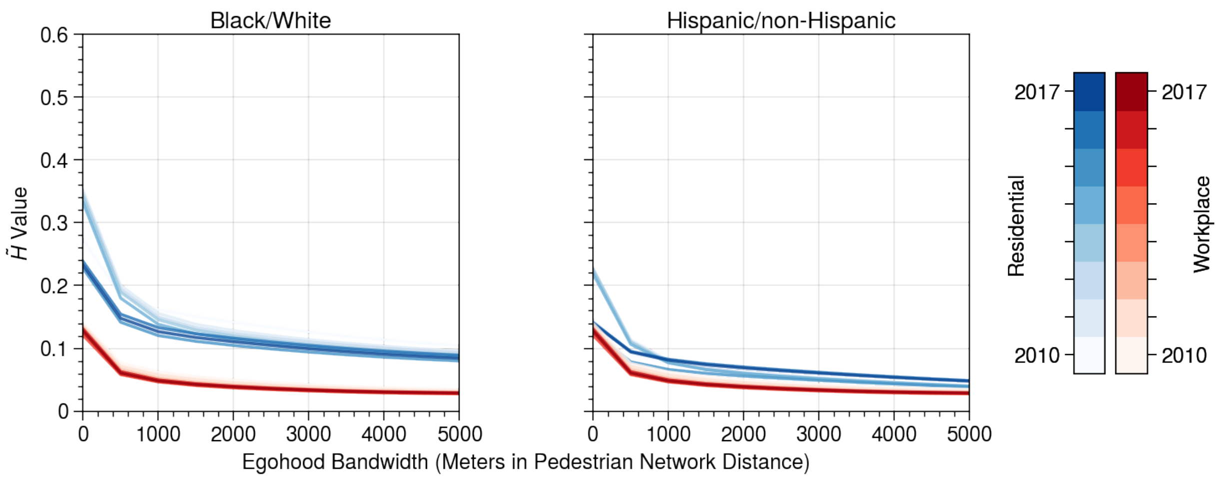

Sacramento--Roseville--Arden-Arcade, CA Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
2017
2010
Residential
Workplace


San Antonio-New Braunfels, TX Metro Area
Segregation Profiles
Black/White
Hispanic/non-Hispanic
$\tilde{H}$ Value
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1000
2000
3000
4000
5000
Egohood Bandwidth (Meters in Pedestrian Network Distance)
2017
2010
Residential
Workplace

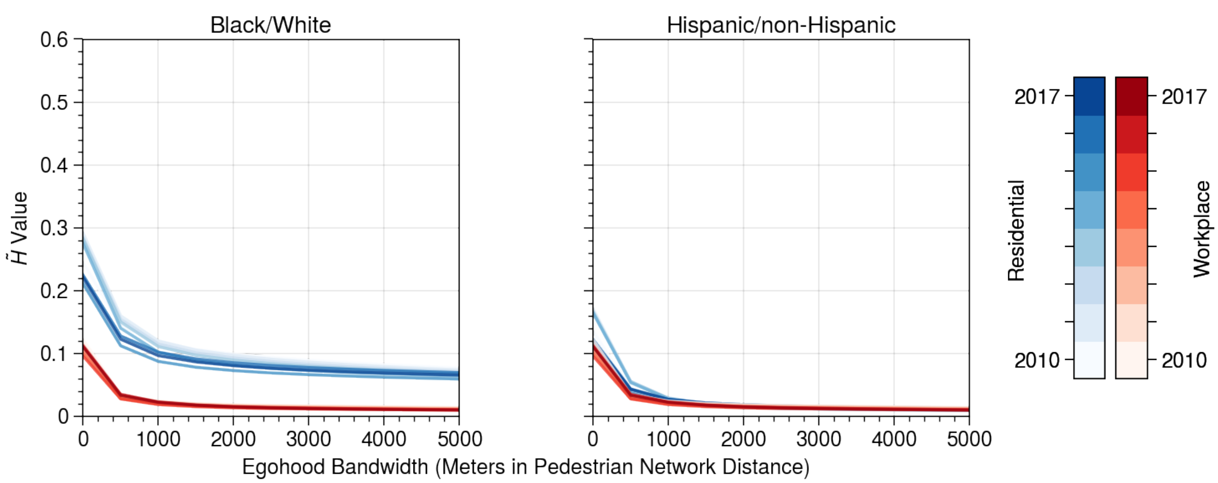
San Diego-Carlsbad, CA Metro Area
Segregation Profiles



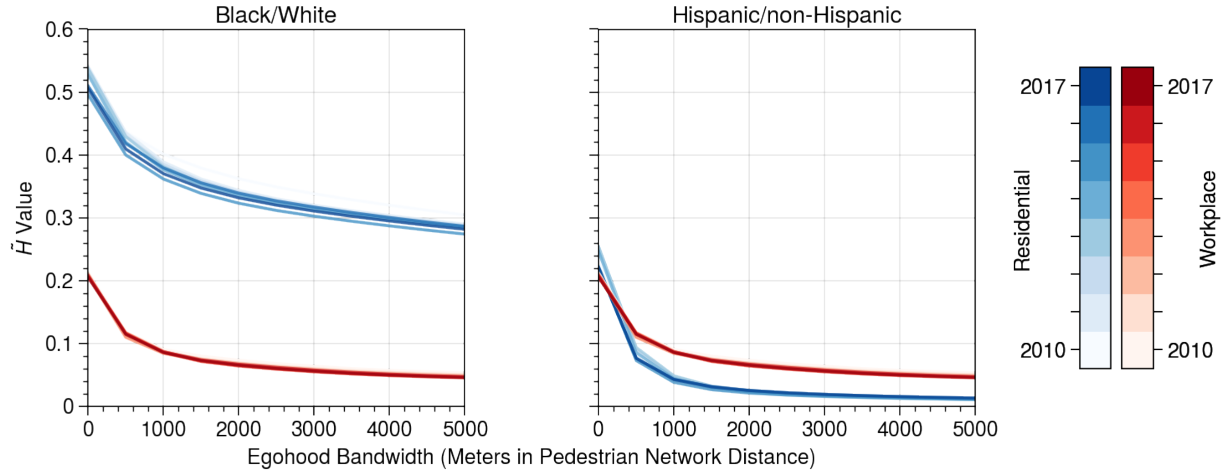
San Francisco-Oakland-Hayward, CA Metro Area
Segregation Profiles



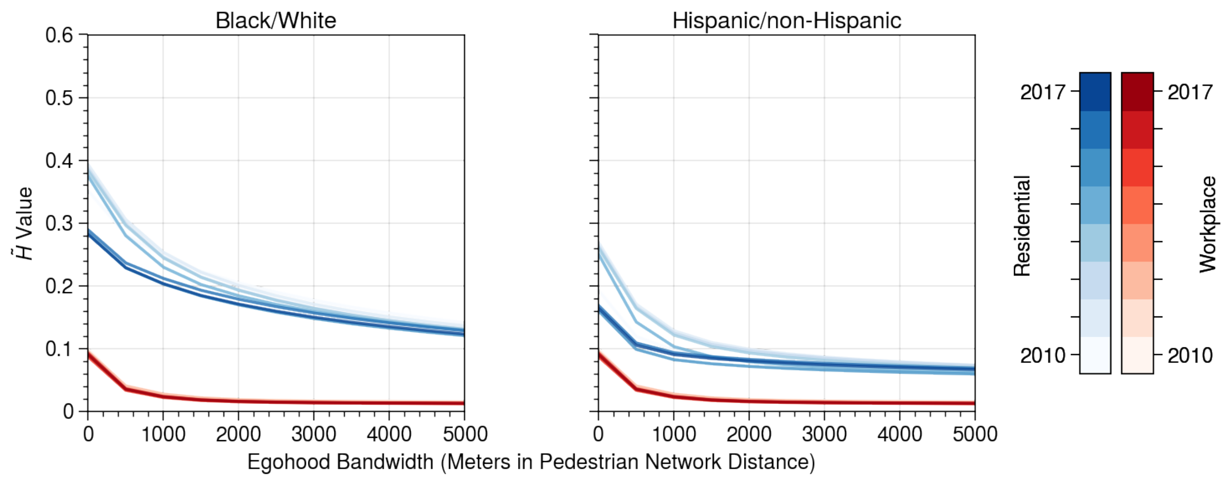
Seattle-Tacoma-Bellevue, WA Metro Area
Segregation Profiles



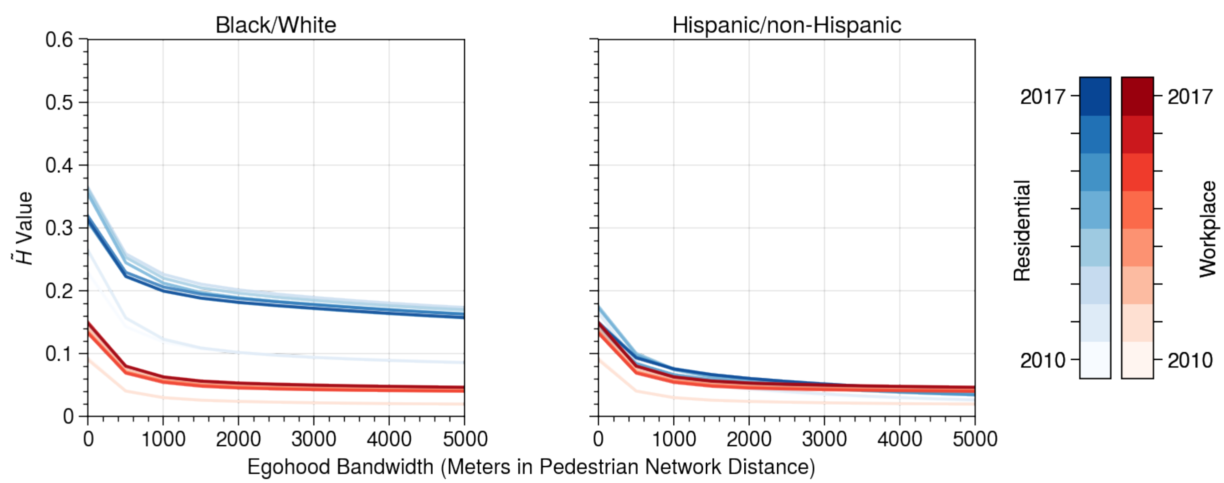
St. Louis, MO-IL Metro Area
Segregation Profiles



Tampa-St. Petersburg-Clearwater, FL Metro Area
Segregation Profiles



Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area
Segregation Profiles



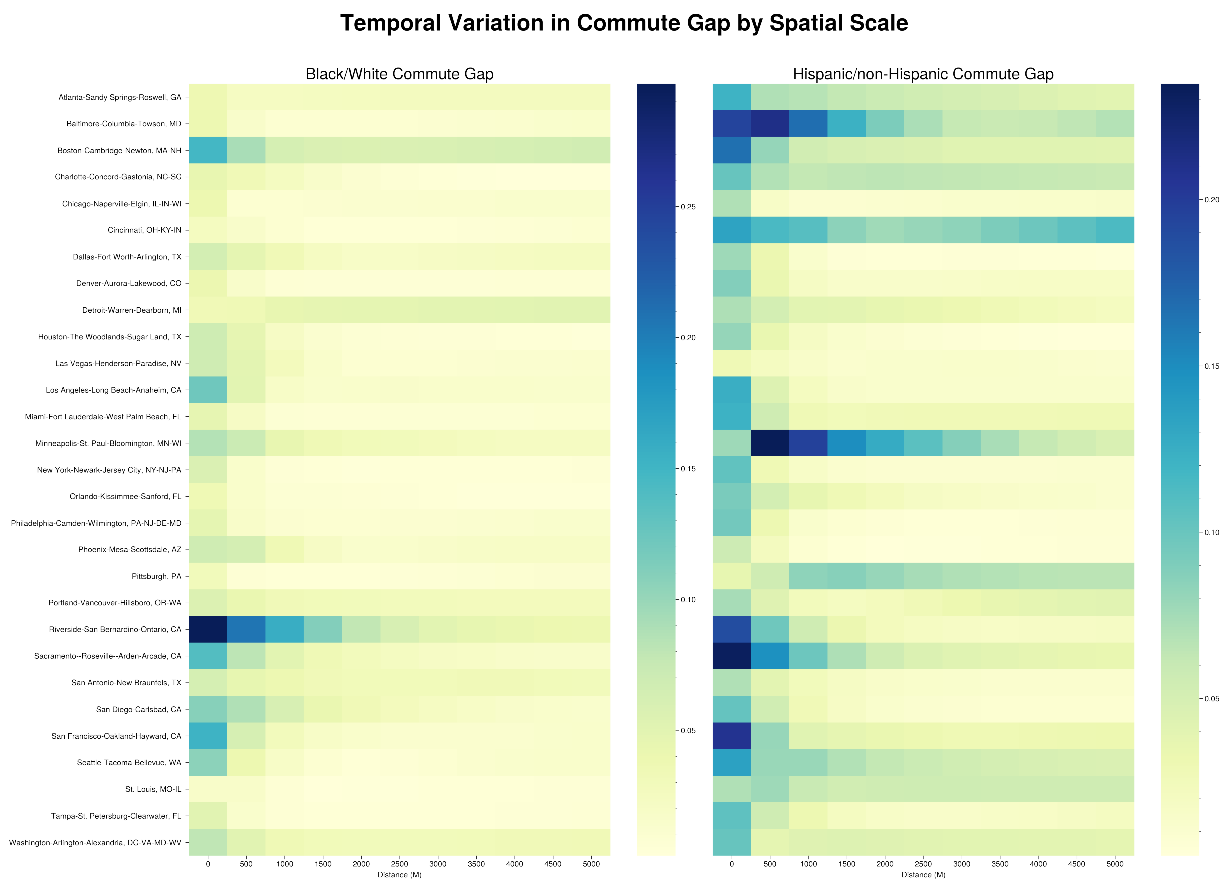


Figure 8: Commute Gap Heatmaps

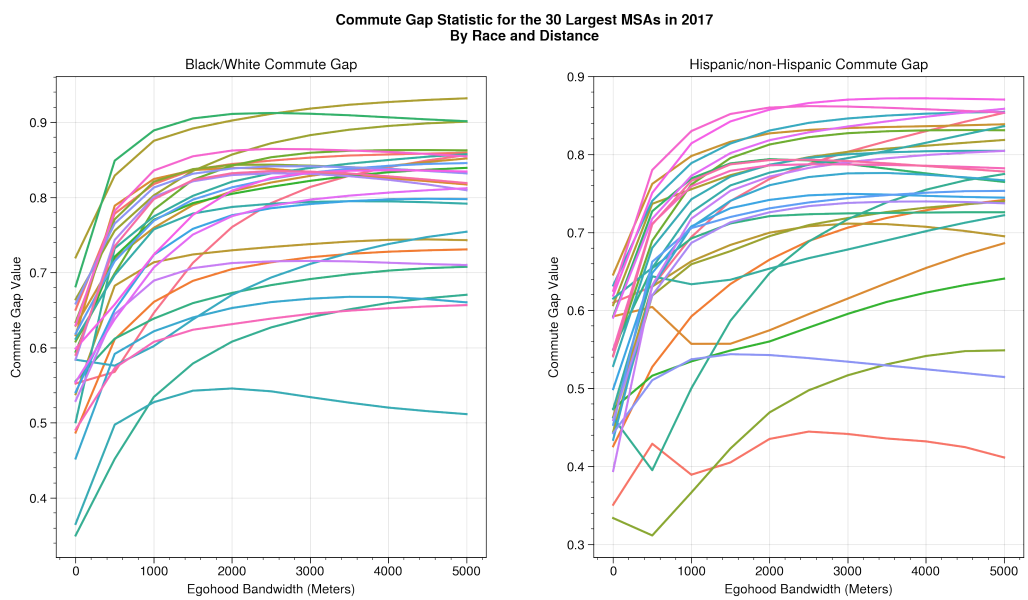


Figure 9: Commute Gap Profiles

	2010	2011	2012	2013	2014	2015	2016	2017
Atlanta-Sandy Springs-Roswell, GA Metro Area	0.651	0.582	0.579	0.57	0.578	0.633	0.653	0.647
Baltimore-Columbia-Towson, MD Metro Area	0.559	0.508	0.507	0.502	0.51	0.538	0.545	0.54
Boston-Cambridge-Newton, MA-NH Metro Area	0.421	0.639	0.611	0.61	0.611	0.631	0.629	0.63
Charlotte-Concord-Gastonia, NC-SC Metro Area	0.51	0.459	0.468	0.466	0.501	0.556	0.576	0.565
Chicago-Naperville-Elgin, IL-IN-WI Metro Area	0.735	0.707	0.703	0.7	0.696	0.733	0.737	0.735
Cincinnati, OH-KY-IN Metro Area	0.54	0.514	0.518	0.509	0.517	0.538	0.549	0.54
Dallas-Fort Worth-Arlington, TX Metro Area	0.51	0.445	0.459	0.454	0.452	0.513	0.522	0.511
Denver-Aurora-Lakewood, CO Metro Area	0.7	0.671	0.674	0.662	0.658	0.687	0.708	0.702
Detroit-Warren-Dearborn, MI Metro Area	0.771	0.729	0.715	0.705	0.711	0.758	0.757	0.752
Houston-The Woodlands-Sugar Land, TX Metro Area	0.586	0.515	0.513	0.506	0.51	0.57	0.577	0.564
Las Vegas-Henderson-Paradise, NV Metro Area	0.444	0.44	0.444	0.429	0.434	0.444	0.444	0.427
Los Angeles-Long Beach-Anaheim, CA Metro Area	0.733	0.641	0.638	0.629	0.626	0.719	0.743	0.733
Miami-Fort Lauderdale-West Palm Beach, FL Metro Area	0.699	0.632	0.628	0.623	0.631	0.706	0.732	0.729
Minneapolis-St. Paul-Bloomington, MN-WI Metro Area	0.416	0.394	0.395	0.397	0.399	0.412	0.416	0.41
New York-Newark-Jersey City, NY-NJ-PA Metro Area	0.688	0.66	0.655	0.647	0.648	0.684	0.698	0.696
Orlando-Kissimmee-Sanford, FL Metro Area	0.592	0.531	0.537	0.524	0.55	0.624	0.649	0.661
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area	0.626	0.607	0.603	0.602	0.602	0.623	0.629	0.631
Phoenix-Mesa-Scottsdale, AZ Metro Area	0.339	0.319	0.32	0.317	0.308	0.373	0.383	0.371
Pittsburgh, PA Metro Area	0.545	0.513	0.509	0.505	0.525	0.525	0.528	0.533
Portland-Vancouver-Hillsboro, OR-WA Metro Area	0.424	0.377	0.368	0.359	0.357	0.366	0.39	0.38
Riverside-San Bernardino-Ontario, CA Metro Area	0.398	0.216	0.222	0.222	0.224	0.41	0.423	0.416
Sacramento–Roseville–Arden-Arcade, CA Metro Area	0.593	0.482	0.481	0.481	0.483	0.589	0.602	0.605
San Antonio-New Braunfels, TX Metro Area	0.468	0.416	0.416	0.403	0.389	0.439	0.473	0.442
San Diego-Carlsbad, CA Metro Area	0.519	0.404	0.405	0.398	0.409	0.495	0.53	0.512
San Francisco-Oakland-Hayward, CA Metro Area	0.615	0.517	0.517	0.509	0.518	0.607	0.619	0.612
Seattle-Tacoma-Bellevue, WA Metro Area	0.568	0.493	0.49	0.488	0.481	0.553	0.568	0.559
St. Louis, MO-IL Metro Area	0.733	0.697	0.7	0.696	0.708	0.718	0.718	0.72
Tampa-St. Petersburg-Clearwater, FL Metro Area	0.555	0.492	0.485	0.487	0.507	0.578	0.595	0.589
Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area	0.627	0.566	0.696	0.695	0.694	0.734	0.738	0.735

Table 2: Black/White Residential Macro-Micro Segregation Ratio

	2010	2011	2012	2013	2014	2015	2016	2017
Atlanta-Sandy Springs-Roswell, GA Metro Area	0.353	0.326	0.329	0.323	0.325	0.361	0.417	0.419
Baltimore-Columbia-Towson, MD Metro Area	0.268	0.229	0.226	0.237	0.238	0.279	0.319	0.339
Boston-Cambridge-Newton, MA-NH Metro Area	0.474	0.594	0.558	0.56	0.566	0.61	0.633	0.635
Charlotte-Concord-Gastonia, NC-SC Metro Area	0.228	0.224	0.222	0.223	0.245	0.275	0.327	0.321
Chicago-Naperville-Elgin, IL-IN-WI Metro Area	0.624	0.586	0.585	0.588	0.583	0.647	0.651	0.654
Cincinnati, OH-KY-IN Metro Area	0.199	0.202	0.214	0.211	0.208	0.235	0.265	0.252
Dallas-Fort Worth-Arlington, TX Metro Area	0.534	0.449	0.459	0.452	0.46	0.552	0.577	0.579
Denver-Aurora-Lakewood, CO Metro Area	0.545	0.514	0.51	0.511	0.506	0.573	0.59	0.59
Detroit-Warren-Dearborn, MI Metro Area	0.516	0.469	0.486	0.468	0.465	0.526	0.57	0.562
Houston-The Woodlands-Sugar Land, TX Metro Area	0.585	0.503	0.512	0.504	0.517	0.603	0.619	0.617
Las Vegas-Henderson-Paradise, NV Metro Area	0.604	0.656	0.651	0.646	0.63	0.651	0.688	0.691
Los Angeles-Long Beach-Anaheim, CA Metro Area	0.655	0.548	0.551	0.547	0.546	0.66	0.674	0.668
Miami-Fort Lauderdale-West Palm Beach, FL Metro Area	0.872	0.786	0.786	0.772	0.774	0.87	0.901	0.9
Minneapolis-St. Paul-Bloomington, MN-WI Metro Area	0.34	0.315	0.319	0.311	0.296	0.309	0.338	0.336
New York-Newark-Jersey City, NY-NJ-PA Metro Area	0.629	0.58	0.582	0.581	0.578	0.631	0.645	0.642
Orlando-Kissimmee-Sanford, FL Metro Area	0.58	0.486	0.516	0.5	0.519	0.65	0.683	0.684
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area	0.592	0.561	0.565	0.558	0.578	0.611	0.631	0.629
Phoenix-Mesa-Scottsdale, AZ Metro Area	0.615	0.577	0.577	0.572	0.568	0.648	0.678	0.678
Pittsburgh, PA Metro Area	0.193	0.188	0.17	0.172	0.161	0.199	0.19	0.192
Portland-Vancouver-Hillsboro, OR-WA Metro Area	0.329	0.318	0.32	0.312	0.326	0.364	0.398	0.387
Riverside-San Bernardino-Ontario, CA Metro Area	0.54	0.351	0.355	0.349	0.355	0.608	0.626	0.627
Sacramento–Roseville–Arden-Arcade, CA Metro Area	0.464	0.321	0.325	0.325	0.33	0.506	0.511	0.501
San Antonio-New Braunfels, TX Metro Area	0.673	0.558	0.559	0.536	0.58	0.67	0.69	0.676
San Diego-Carlsbad, CA Metro Area	0.681	0.575	0.579	0.571	0.601	0.708	0.726	0.719
San Francisco-Oakland-Hayward, CA Metro Area	0.508	0.406	0.405	0.404	0.424	0.548	0.574	0.567
Seattle-Tacoma-Bellevue, WA Metro Area	0.217	0.193	0.201	0.194	0.205	0.259	0.314	0.322
St. Louis, MO-IL Metro Area	0.147	0.146	0.152	0.141	0.146	0.168	0.195	0.196
Tampa-St. Petersburg-Clearwater, FL Metro Area	0.587	0.461	0.467	0.452	0.462	0.628	0.66	0.663
Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area	0.356	0.341	0.394	0.394	0.397	0.451	0.471	0.481

Table 3: Hispanic/non-Hispanic Residential Macro-Micro Segregation Ratio

metro	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
Atlanta-Sandy Springs-Ro	0.07	0.062	0.048	0.038	0.032	0.03	0.03	0.031	0.032	0.034	0.035
Baltimore-Columbia-T	0.078	0.06	0.047	0.041	0.039	0.039	0.04	0.041	0.042	0.043	0.044
Boston-Cambridge-Newt	0.203	0.191	0.094	0.06	0.048	0.043	0.041	0.042	0.043	0.046	0.049
Charlotte-Concord-Gaston	0.109	0.115	0.094	0.073	0.058	0.048	0.041	0.036	0.033	0.031	0.03
Chicago-Naperville-Elgin,	0.084	0.056	0.048	0.046	0.046	0.046	0.046	0.047	0.047	0.047	0.047
Cincinnati,	0.057	0.07	0.066	0.064	0.065	0.063	0.06	0.057	0.054	0.051	0.048
Dallas-Fort Worth-Arli	0.124	0.097	0.068	0.054	0.049	0.047	0.046	0.046	0.046	0.046	0.047
Denver-Aurora-Lak	0.073	0.068	0.059	0.06	0.062	0.062	0.062	0.061	0.061	0.06	0.059
Detroit-Warren-Dea	0.081	0.064	0.06	0.06	0.06	0.062	0.063	0.064	0.065	0.066	0.067
Houston-The Woodlands-Sugar	0.11	0.102	0.084	0.076	0.073	0.073	0.073	0.074	0.074	0.074	0.074
Las Vegas-Henderson-Par	0.07	0.041	0.039	0.041	0.043	0.045	0.046	0.046	0.045	0.045	0.045
Los Angeles-Long Beach-An	0.173	0.115	0.085	0.08	0.078	0.077	0.077	0.077	0.077	0.077	0.077
Miami-Fort Lauderdale-West Palm	0.112	0.084	0.066	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063
Minneapolis-St. Paul-Bloomingt	0.039	0.048	0.049	0.048	0.047	0.047	0.046	0.045	0.044	0.043	0.042
New York-Newark-Jersey City,	0.112	0.094	0.091	0.09	0.09	0.089	0.089	0.088	0.088	0.087	0.087
Orlando-Kissimmee-Sa	0.133	0.112	0.075	0.062	0.056	0.053	0.05	0.048	0.046	0.046	0.045
Philadelphia-Camden-Wilmington, PA	0.074	0.054	0.048	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.047
Phoenix-Mesa-Scott	0.11	0.107	0.07	0.049	0.041	0.039	0.039	0.039	0.04	0.04	0.041
Pitts	0.048	0.053	0.051	0.05	0.051	0.051	0.051	0.051	0.051	0.05	0.05
Portland-Vancouver-Hillsbo	0.082	0.095	0.101	0.11	0.114	0.117	0.118	0.119	0.119	0.118	0.118
Riverside-San Bernardino-On	0.333	0.353	0.262	0.169	0.11	0.08	0.066	0.057	0.051	0.046	0.044
Sacramento–Roseville–Arden-A	0.17	0.132	0.075	0.054	0.047	0.044	0.044	0.044	0.044	0.045	0.045
San Antonio-New Brau	0.143	0.137	0.129	0.12	0.116	0.115	0.116	0.118	0.119	0.119	0.12
San Diego-Car	0.179	0.189	0.139	0.12	0.113	0.108	0.103	0.1	0.097	0.095	0.093
San Francisco-Oakland-Ha	0.19	0.131	0.102	0.097	0.096	0.094	0.092	0.09	0.088	0.085	0.083
Seattle-Tacoma-Bel	0.129	0.12	0.108	0.106	0.104	0.102	0.098	0.093	0.089	0.085	0.082
St. Lou	0.032	0.031	0.031	0.033	0.033	0.033	0.032	0.032	0.031	0.031	0.03
Tampa-St. Petersburg-Clear	0.146	0.122	0.091	0.078	0.071	0.066	0.061	0.058	0.055	0.053	0.051
Washington-Arlington-Alexandria, DC	0.154	0.201	0.228	0.24	0.247	0.251	0.253	0.254	0.254	0.254	0.254

Table 4: Black/White Residential $\tilde{H}$ Coef of Variation by Scale

metro	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
Atlanta-Sandy Springs-Roswell, GA	0.117	0.109	0.102	0.087	0.076	0.072	0.072	0.073	0.075	0.076	0.078
Baltimore-Columbia-Towson, MD	0.142	0.136	0.104	0.09	0.087	0.088	0.091	0.095	0.099	0.103	0.107
Boston-Cambridge-Newton, MA-NH	0.279	0.288	0.217	0.192	0.184	0.18	0.179	0.18	0.183	0.186	0.191
Charlotte-Concord-Gastonia, NC-SC	0.153	0.188	0.181	0.156	0.12	0.099	0.087	0.079	0.074	0.072	0.071
Chicago-Naperville-Elgin, IL-IN-WI	0.145	0.064	0.043	0.04	0.039	0.039	0.039	0.039	0.039	0.039	0.039
Cincinnati, OH-KY-IN	0.078	0.091	0.093	0.099	0.111	0.119	0.122	0.122	0.121	0.12	0.119
Dallas-Fort Worth-Arlington, TX	0.167	0.121	0.072	0.055	0.05	0.048	0.048	0.047	0.047	0.048	0.048
Denver-Aurora-Lakewood, CO	0.131	0.098	0.066	0.057	0.054	0.053	0.051	0.051	0.05	0.05	0.049
Detroit-Warren-Dearborn, MI	0.132	0.091	0.079	0.081	0.082	0.082	0.082	0.082	0.081	0.081	0.081
Houston-The Woodlands-Sugar Land, TX	0.153	0.114	0.078	0.06	0.052	0.048	0.046	0.044	0.043	0.042	0.041
Las Vegas-Henderson-Paradise, NV	0.066	0.068	0.075	0.078	0.08	0.081	0.082	0.082	0.083	0.083	0.083
Los Angeles-Long Beach-Anaheim, CA	0.205	0.106	0.06	0.055	0.055	0.055	0.055	0.056	0.055	0.055	0.055
Miami-Fort Lauderdale-West Palm Beach, FL	0.128	0.114	0.122	0.128	0.13	0.131	0.131	0.131	0.131	0.13	0.129
Minneapolis-St. Paul-Bloomington, MN-WI	0.067	0.076	0.067	0.071	0.075	0.079	0.083	0.087	0.089	0.091	0.093
New York-Newark-Jersey City, NY-NJ-PA	0.164	0.086	0.072	0.07	0.07	0.07	0.069	0.069	0.068	0.067	0.067
Orlando-Kissimmee-Sanford, FL	0.169	0.155	0.118	0.093	0.075	0.063	0.054	0.049	0.047	0.046	0.046
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.111	0.051	0.035	0.034	0.034	0.035	0.035	0.036	0.036	0.037	0.037
Phoenix-Mesa-Scottsdale, AZ	0.117	0.093	0.078	0.076	0.076	0.075	0.075	0.074	0.074	0.074	0.073
Pittsburgh, PA	0.072	0.125	0.134	0.131	0.126	0.123	0.12	0.117	0.114	0.111	0.109
Portland-Vancouver-Hillsboro, OR-WA	0.095	0.074	0.05	0.047	0.047	0.049	0.05	0.05	0.05	0.05	0.049
Riverside-San Bernardino-Ontario, CA	0.358	0.292	0.184	0.114	0.08	0.066	0.06	0.058	0.057	0.057	0.057
Sacramento–Roseville–Arden-Arcade, CA	0.294	0.264	0.171	0.113	0.082	0.069	0.065	0.06	0.057	0.055	0.054
San Antonio-New Braunfels, TX	0.175	0.166	0.14	0.121	0.108	0.101	0.098	0.096	0.096	0.096	0.096
San Diego-Carlsbad, CA	0.167	0.107	0.056	0.045	0.044	0.045	0.045	0.045	0.044	0.044	0.044
San Francisco-Oakland-Hayward, CA	0.256	0.122	0.064	0.071	0.078	0.083	0.086	0.089	0.092	0.094	0.097
Seattle-Tacoma-Bellevue, WA	0.162	0.153	0.108	0.098	0.106	0.117	0.128	0.137	0.145	0.151	0.157
St. Louis, MO-IL	0.065	0.094	0.08	0.074	0.08	0.084	0.086	0.088	0.09	0.092	0.094
Tampa-St. Petersburg-Clearwater, FL	0.227	0.223	0.167	0.132	0.113	0.101	0.092	0.086	0.08	0.076	0.072
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.092	0.085	0.102	0.117	0.129	0.138	0.146	0.153	0.158	0.163	0.167

Table 5: Hispanic/non-Hispanic Residential $\tilde{H}$ Coef of Variation by Scale