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Are Central Cities Poor and Non-White?

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Abstract

For much of the 20th century, America's central cities were viewed as synonymous with economic and social hardship, often used as proxy for low-income communities of color. Since the 1990s, however, many metropolitan areas have seen a resurgence of interest in central city neighborhoods. Theoretical models of income sorting lead to ambiguous predictions about where households of different income levels will live within metropolitan areas. In this paper, we explore intra-city spatial patterns of income and race for U.S. metropolitan areas, focusing particularly on the locations of low-income and minority neighborhoods. Results indicate that, on average, income and white population shares increase with distance to city centers. However, many centrally located neighborhoods are neither low-income nor majority non-white, while low-income and minority neighborhoods are spatially dispersed across most metropolitan areas.

Keywords: Income sorting; racial segregation; urban spatial structure; neighborhood choice; housing policy
JEL codes: I3, J1, R1, R2

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1) Introduction

During most of the 20th century, America's urban areas followed clear patterns of income sorting: neighborhoods near the city center tended to house lower-income and non-white residents, while affluent, mostly white households located in outlying neighborhoods and suburbs. This spatial income pattern is so prevalent in the U.S. that the terms "central city" and "inner city" are often used as proxies for neighborhood socioeconomic status as much as geographic location (Jargowsky 1997; Wilson 1987). And yet, both empirical evidence and urban theory suggest that other income-space equilibria are possible. For instance, many European cities have relatively rich centers and poorer suburbs. Although urban economic theory predicts that households will cluster by income, models yield ambiguous predictions about the relationship between income and distance from city center. In this paper, we examine spatial patterns of income and race across U.S. metropolitan areas, to explore whether neighborhoods close to the central business district (CBD) are more likely to be occupied by low-income or non-white residents. How spatially correlated are income and racial/ethnic composition? How do these correlations vary within and across metropolitan areas?

Urban economics models make a number of predictions about how and why households will sort across space, but these predictions are somewhat ambiguous about where low-income households will locate. The standard urban model (SUM) predicts that firms will outbid households for land near the CBD and households will outbid firms for land near the urban fringe (Alonso 1964; Brueckner 1987; Mills 1967; Muth 1969). Where low-income households locate within a city, relative to either firms or higher-income households, depends on several factors: whether the quantity of land per housing unit is allowed to vary over space (i.e. differences in lot size and housing density), commuting costs, and correlations between income and preferences for housing density or location-based amenities (natural, private, and public).

Prior empirical research has documented multiple equilibria for household sorting by income within a city, and posited some hypotheses for these different outcomes. Many European cities have high levels of cultural amenities – such as museums, parks, and historic sites -- near the city center that attract higher-income households (Brueckner et al 1999, Koster et al 2014, Lin and Lee 2015). Brueckner and Rosenthal (2009) and Rosenthal (2007) find that the age of the housing stock influences city-suburb income sorting. Over the past 25 years, some U.S. cities have seen increased movement by higher income households into central city neighborhoods and an increasing "suburbanization of poverty" (Baum-Snow and Hartley 2016; Couture and Handbury 2016; Ellen and O'Regan 2008; Ellen and O'Regan 2011; Kneebone and Holmes 2016; McKinnish, Walsh and White 2010). Housing, urban and transportation policies can also influence spatial income patterns. French cities have tended to build subsidized social housing on the urban fringes (banlieues) while most public housing in the U.S. was built in central cities (Whitehead and Scanlon 2007). Glaeser et al (2008) highlight the absence of reliable public transportation in deterring lower income households moving to suburbs. While federal policies are likely to influence spatial patterns of income similarly across cities within a country, state and local policies – along with locally-specific historical events – contribute to differences across metropolitan areas, which is the main focus of this paper.

Household spatial sorting by income has a relatively straightforward explanation: income correlates with the ability to pay for housing, including capitalized value of local public goods and private amenities (Tiebout 1956). By contrast, spatial variation in neighborhood racial/ethnic composition may reflect a number of factors. One mechanism for sorting by race/ethnicity within U.S. cities is the presence of long-standing racial gaps in income and wealth

(Blau and Graham 1990; Hedman and Galster 2013). Moreover, an extensive literature has documented racial discrimination in the housing and mortgage markets (Bayer et al 2016; Cutler and Glaeser 1997; Ellen 2000; Kain 1968; Massey and Denton 1993; Munnell et al 1996; Ross and Yinger 2002; Turner and Mikelsons 1992; Yinger 1991). Most of the literature on racial income gaps and housing discrimination focuses on differences in outcomes between African-Americans and non-Hispanic whites; there is a small but growing literature looking at wealth and housing gaps for Hispanics (Bayer et al 2016; Ross and Turner 2005).

In this paper, we examine where low-income and minority neighborhoods are located within U.S. metropolitan areas. We investigate the correlations between income and distance to the CBD, between income and racial/ethnic composition, and clustering among low-income and minority neighborhoods. Using tract-level census data for 24 large metropolitan statistical areas (MSAs), we present descriptive statistics and graphical analysis of the correlation between income, race/ethnicity, and distance to the CBD, focusing particularly on neighborhoods in the lowest income quartile within each MSA.[1] To further explore the nuances of these relationships across MSAs with different underlying spatial structures and varying ethnic composition, we estimate a series of locally smoothed regressions for four MSAs: Atlanta, Detroit, Los Angeles and Washington. Our paper makes several contributions to the literature on income sorting and residential segregation. First, we demonstrate wide variation in socio-spatial correlations across U.S. metropolitan areas. Second, we highlight different spatial patterns among black, Hispanic and Asian neighborhoods within and across metropolitan areas; this adds to the relatively small housing literature on Hispanics and Asians. Third, the nonparametric estimation approach

[1] We use the 2013 definitions of MSAs throughout this analysis.

illustrates the nuances and complexities of spatial patterns, which may be lost in traditional parametric estimations.

Several distinct patterns of income, race and location emerge from the results. We find that distance from CBD is correlated with neighborhood income and race, but the direction, steepness, and shape of the correlations vary within and across metropolitan areas. On average across all MSAs, neighborhood income increases with distance to the CBD, consistent with prior empirical research. However, not all MSAs fit the poor city-rich suburb model: among our four focus areas, Detroit and Los Angeles have clearly upward sloping income-distance correlations, while Atlanta's correlation is nearly flat and Washington's is non-monotonic, with local maxima near the CBD and farther away. Although on average, tracts near the CBD have larger minority populations, these patterns vary by ethnic group and city. Black residents are disproportionately likely to live within 10 miles of the CBD, while Asian residents are more likely to cluster beyond 10 miles from the CBD. Spatial patterns of Hispanics vary across MSAs. Exploring the reasons behind these within- and across-city variations is an important area for future research; in the conclusion, we outline several potential extensions of this research.

2) Empirical approach and data description

This paper explores the variation in spatial patterns of low-income and minority urban neighborhoods across U.S. metropolitan areas. Using kernel-weighted locally smoothed regressions, we examine where low-income neighborhoods are located within large metropolitan areas, relative to the CBD, and whether income and race are spatially correlated. The analysis is descriptive and intended to identify patterns; we do not test for causal relationships, but in the paper's final section we outline several hypotheses that could be explored in future work.

2.1) Geographic sample selection

The analysis presents results for a set of 24 large MSAs, selected to provide diversity across several dimensions, including geographic region (at least two MSAs from each of the nine Census divisions), population size, average income, and racial/ethnic composition. The list of sample MSAs and summary characteristics is shown in Table 1. Using 24 diverse MSAs allows us to explore the range of spatial-income-race correlations across the U.S., and to ask whether any regional patterns among these MSAs are apparent. However, the large sample necessarily limits depth of analysis for any particular MSA, so we also select four MSAs for more detailed exploration: Atlanta, Detroit, Los Angeles and Washington. These MSAs – one from each of the four large Census regions -- were chosen because they differ along two essential dimensions that will affect spatial patterns of income and race. First, the four MSAs have different underlying spatial structures, based on topographical features (water bodies and mountains) and degree of employment centralization (Giuliano and Small 1991). Second, they vary substantially in the MSA-level racial and ethnic composition, as shown in Table 1. One of the purposes of this paper is to develop additional hypotheses on what MSA-level characteristics might affect spatial patterns of income and race.

In this paper, we follow much of the urban economics literature in defining neighborhoods as census tracts.[2] For the income analysis, we assign all tracts to income quartiles within the MSA based on median household income, and refer to tracts in the bottom quartile as "low-income." Because our question is the intra-metropolitan spatial distribution of income, measuring tract income relative to the MSA is more appropriate than national level income measures (for instance, quartiles of the national income distribution). Setting standards

[2] Hardman and Ionnides (2003) document substantial within-tract income diversity, but this method relies of micro-level data not easily available.

at the MSA level most accurately captures households' effective purchasing power, particularly for goods such as housing and transportation that vary substantially across cities. Households in high-cost MSAs may be considered relatively affluent in the national income distribution, but face challenges affording essential goods and services.[3] We also present some results using tract poverty rates (which are highly correlated with tract median incomes), and using Gini coefficients as a proxy for within-tract income dispersion.

Neighborhood income and racial/ethnic composition are measured using the 2010-2014 ACS data. Variable definitions are shown in Table 2. Tract income is measured by median household income, percent of population below the federal poverty line and Gini coefficient. Racial and ethnic composition are measured as the shares of non-Hispanic white, black, and Asian residents in each tract, and the share of Hispanic residents (all races). Because each tract has roughly the same population, using tracts as the unit of analysis effectively weights each person in our study MSAs equally. Larger MSAs have a much larger number of tracts, and so the impact that MSAs have on the pooled descriptive statistics increases with their population. This is particularly notable on racial/ethnic composition, because the largest MSAs tend to have the highest non-white population shares (especially Hispanic, given the prevalence of large MSAs in California and Texas). Although assigning equal weights per person is a reasonable aggregation approach, the varied size of MSAs and the associated concern about overemphasizing the largest cities in the results is another rationale for conducting most of the analysis separately by MSA rather than pooling them.

2.2) Defining the Central Business District

[3] There is an extensive literature on whether relative or absolute income matters for individual utility, but most of this deals with the household or individual level rather than measurement for geographic areas. (See, for instance, Clark et al 2008, Gerdtham and Johannesson 2002, Dynan and Ravina 2007, Dodini 2016.)

An important question for measuring spatial patterns is the identification of the CBD. Although the CBD is an essential concept in the standard urban model, the empirical urban literature has not reached a consensus on how to define and measure CBDs in practice. We follow prior researchers (Asabere and Huffman 1991, Atack and Margo 1998) in using the location of City Hall for the primary central city within each MSA.[4] This approach has several advantages: the addresses of City Halls are readily available, calculating distances from City Hall to other locations can be easily done using latitude-longitude coordinates, the location of City Hall is constant over very long periods of time, and it requires few assumptions by the analyst. Another fairly common approach to defining the CBD is to use estimates from the 1982 Census of Retail Trade, in which local business leaders were surveyed about "major retail centers" in their respective metropolitan areas to subjectively define the CBD using local knowledge (Census Bureau 1982). Additionally, several papers use disaggregated employment data to construct employment centers, designating either the largest or densest employment center within an MSA as the CBD (Giuliano and Small 1991; McMillen 2001; Brown et al 2016; Redfearn 2007). Both of these methods define the CBD as an area of variable size rather than a unique point. While this has some intuitive appeal, it complicates measurement of distance from tracts to the CBD; for instance, should distances be measured from the nearest point on the boundary or from the centroid of the CBD area. Moreover, defining employment centers has onerous data requirements due to highly disaggregated employment counts, and requires the analyst to make additional assumptions, such as choosing the appropriate employment cluster size, contiguity of tracts, etc. Because our primary purpose in defining the CBD is to estimate

[4] Within MSAs, OMB identifies certain "principal cities" that are large employment centers. Not all incorporated cities within an MSA are designated as principal cities. The primary central city is the one listed first in the MSA name (i.e., Los Angeles is the primary central city for the Los Angeles-Long Beach-Anaheim MSA). Current principal city designations are available from the Census: http://www.census.gov/population/metro/data/def.html.

distance of census tracts across the MSA relative to a central point, it is not necessary for our identified CBD to be the highest employment density location. As long as City Hall is located in or near what would colloquially be referred to as "downtown", it will be sufficient to estimate MSA-wide distance patterns.

We use Google maps to locate City Hall for the primary designated central city within each MSA, and calculate the distance from City Hall to the centroid of each census tract using tract latitude and longitude coordinates provided by Census TIGER files. As a robustness check, we compare City Hall locations for our four key MSAs to the CBD definitions from the 1982 Census of Retail Trade. In all four cases, City Hall falls well within the boundaries of the polygon mapped by the 1982 CBD. For the size of the MSAs and the distances under consideration (up to 40 miles), measuring tract-CBD distances from one point within the CBD or from the polygon's boundaries will not materially alter estimates. To eliminate spatial outliers on the urban boundary, we drop census tracts with centroids more than 40 miles from the CBD.[5] To observe whether City Hall serves as a reasonable approximation of the CBD with respect to development patterns, we estimate the population density gradient as a function of distance to City Hall for our four featured MSAs. As predicted by the standard urban model, population density slopes downward from City Hall to the urban boundary for all four MSAs (Appendix Figure 1).

Using the City Hall for the primary central city within the MSA implicitly assumes a monocentric urban structure, which has been challenged by a number of scholars (McMillen

[5] Roughly 95 percent of tracts for all 24 MSAs fall within 40 miles of the CBD, although for Miami-Dade FL and Riverside CA, more than 20 percent of tracts are further than 40 miles. We also exclude a small number of tracts with populations under 500 or population densities under 100/square mile (these are mostly very large land area tracts in Western MSAs that include uninhabited desert or forest lands). All substantive results are robust to dropping these tracts.

2001, Agarwal et al 2012, Redfearn 2007). To test the robustness of our results, for our four primary MSAs, we use the same approach to identify the location of major subcenters – City Hall for all designated principal cities within the MSA -- and measure the distance from each census tract to the nearest employment center. Using subcenters substantially compresses the distribution of tract-CBD distances, but the shape of the population density gradient from the nearest center is quite similar to that of the primary CBD (Appendix Figure 2). Therefore for the remainder of the paper we present results based on the distance from tracts to the primary CBD. Examining whether the overall MSA employment structure – number or size of subcenters, for instance, or degree of employment centralization – affects the income-race-distance patterns within that MSA would be an interesting area for future research.

Our choice of linear distance from CBD as the independent variable derives from the standard urban model. However, one possible concern is that linear distance between tracts and CBD may not accurately reflect travel costs (times) between those locations, due to uneven spatial patterns in transportation networks (i.e. proximity to highways versus surface roads). As an additional robustness check, we obtain estimated travel times to the CBD from Google maps for both driving and public transit, for census tracts in the four key MSAs.[6] Within MSAs, linear distance to CBD is highly correlated with both driving time and transit time (correlation coefficients range from 0.84 to 0.95), and the estimated graphical relationship between income and distance is very similar using either travel time measure to linear distance, although somewhat noisier (Appendix Figures 3 and 4).

[6] Driving times were available for all census tracts, and were estimated at the same day and time for all tracts, to avoid variations in traffic volumes. Public transit times are only available for locations where Google maps can draw from a local transit authority that serves the area. Transit times were matched for 95 percent of Los Angeles-area census tracts, 85 percent of Washington, DC tracts, 76 percent of Detroit tracts, and 56 percent of Atlanta tracts.

2.2) Empirical approach

In order to describe the intra-MSA spatial patterns of income and race, we use a variety of descriptive statistics and graphical analyses. The main approach is to estimate kernel-weighted locally smoothed regressions of distance to the CBD and tract income, racial and ethnic composition. The regression lines are overlaid with scatter plots showing tracts by income quartile, to illustrate the location of low-income tracts. Using a nonparametric approach such as locally weighted regression allows us to explore the shapes of underlying relationships, rather than imposing a pre-determined functional form.[7] As the graphs illustrate, many of the relationships are non-linear and non-monotonic; calculating simple correlation coefficients or OLS regressions would incorrectly describe these relationships. For each graph, we consider the following dimensions: average levels (intercepts) of dependent variables, range of both variables (height and width of line/curve), direction and steepness of correlation (slope), overall shape (linearity or curvature, monotonicity), and goodness of fit (dispersion of data points around the fitted function). Collectively, analysis along these dimensions describe the relationships between neighborhood location, income and race/ethnicity. Most figures embed graphs for the four key MSAs, also allowing comparison across these MSAs along each dimension.

We use three approaches to observe whether low-income and minority tracts tend to cluster together, or are dispersed throughout the MSA. First, we construct maps for the four focus MSAs, showing the location of tracts by income and ethnic composition. While the regressions and scatterplots can show correlation of income/ethnicity with distance to CBD, this does not account for differences in the direction (i.e. north-south). The maps allow observation of both distance and direction. Second, we calculate the correlation between tract own income

[7] All kernel-weighted regressions use the default Epanechnikov kernel and are robust to minor variations in degree and bandwidth (results available from authors upon request).

(race/ethnicity) and the income (race/ethnicity) of a tract's five "nearest neighbors", based on pairwise distances between tract centroids for all tracts within an MSA.[8] To measure the similarity between each tract and its neighbors, we calculate the distance-weighted average income and racial/ethnic composition of the five nearest neighbor tracts. Equation 1 shows the calculation of weighted averages:

(Eq. 1) $$income\_nn5_i = \frac{\sum_{j=1}^{5} wt_j * income_j}{\sum_{j=1}^{5} wt_j} \text{ where } wt_j = \frac{1}{|dist_{i-j}|}$$

In this equation, i represents the own tract, j represents neighboring tracts. Spatially weighted averages are generally comparable to a simple average of the five nearest tract characteristics for tracts close to the CBD, but weighted averages vary substantially from unweighted averages for some tracts at the urban fringe, because of larger and more irregular tract shapes. Third, we calculate the share of MSA population within each racial/ethnic group living within three distance bands from the CBD (0-10 miles, 10-20 miles, and 20+ miles). By comparing the share of each MSA's black, Hispanic and Asian residents within each distance band to the share of the MSA's total population in the same band, we can observe whether minorities are disproportionately likely to live near to the CBD. The latter method is particularly useful, given the large differences in racial/ethnic composition across our four key MSAs: Atlanta and Detroit are largely black-white MSAs while Los Angeles is majority Hispanic.

3) Results

The results described below indicate that, on average, neighborhoods near the CBD are more likely to be low-income and have larger non-white populations which is consistent with the

[8] We constrain all nearest neighbor tracts to be within the same MSA, although a few tracts are closer to tracts in adjacent MSAs.

traditional view of the racial/ethnic and income makeup of central cities. However, this average masks the considerable variation within and across MSAs in spatial patterns of income and race/ethnicity. Many of the correlations are non-linear and non-monotonic.

3.1) Describing low income neighborhoods – all MSAs

Income levels both for MSAs and for low-income neighborhoods vary considerably across the 24 sample MSAs (Table 1). MSA-level median tract income ranges from $51,910 in Miami-Dade to $108,136 in Washington. Similarly, there is a wide range of cutoff values for tracts in the bottom income quartile within each MSA – defined as low-income neighborhoods for this analysis. In Dallas, Detroit, Houston and Miami, tracts with median incomes below $41,000 fall into the bottom quartile. By contrast, in Boston, Minneapolis, San Francisco, Seattle and Washington the lowest quartile includes tracts with incomes up to $63,000 or higher.

Pooling the low-income tracts across all 24 MSAs, some consistent differences emerge between the poorest neighborhoods and the upper three quartiles (Table 3). The low-income tracts are generally closer to the CBD than higher income neighborhoods, although the average distance of 10.5 miles is a fairly wide radius. On average, low-income tracts have more than double the population density of higher income tracts. Not only is the average income lower in the bottom quartile (by definition), poverty rates are three times higher than in the top three quartiles. Perhaps less predictably, the Gini coefficient suggests that lower income tracts have relatively higher within-neighborhood income dispersion. Low-income tracts also have larger shares of black and Hispanic populations, but somewhat smaller Asian populations. [9] For most of these variables, standard deviations (not shown) are quite large compared to the mean values, reflecting substantial variation across the sample.

[9] Although the ACS sample sizes are too small to support much analysis, Asians in Los Angeles are more diverse in their countries of origin than in most other MSAs, which may contribute to within-group economic diversity.

Continuing with the pooled MSA analysis, Figure 1 shows the relationship between neighborhood income and distance from the CBD, estimated by kernel-weighted locally smoothed regressions. As discussed in the introduction, theoretical models suggest that multiple equilibria are possible, with higher-income households locating near the CBD to minimize commuting costs and/or be near centralized amenities, or locating far from the CBD to maximize housing consumption – either lot size or neighborhood amenities, such as school quality or low crime. Pooling all tracts across the 24 MSAs shows a non-monotonic relationship: within five miles of the CBD, income decreases with distance, then the slope reverses direction, with tract incomes increasing up to about 25 miles from the CBD, then flattening out (Figure 1). In addition to the estimated regression between distance and income, Figure 1 shows a scatterplot of individual tracts, colored by income quartile within MSA, ranging from the red dots showing the lowest-income tracts to the light gray dots showing the highest income tracts[10]. About 28 percent of the lowest-income neighborhoods are located within 5 miles from the CBD, and 34 percent are located between 5 and 10 miles of the CBD, but 24 percent are located more than 20 miles away – essentially the outer suburbs for most of these MSAs. That is, low-income neighborhoods exist both at central locations where the SUM predicts land values will be high, and at the urban fringe where land values and housing costs are low but commuting costs are relatively high.[11] The highest income tracts are most prevalent beyond 10 miles from the CBD, but about 12 percent of the richest neighborhoods are within five miles of the CBD. Of course,

[10] Because we assign tracts to quartiles within MSA, the cutoffs are different across the 24 MSAs. For this reason, at a given income level in Figure 1, tracts may be in different income quartiles if they are from different MSAs. This overlap in the income quartiles occurs only in Figure 1; by definition there can be no overlap in the income quartiles for the subsequent MSA-specific graphs.

[11] We also estimate these graphs using housing rents and estimated owner-occupied housing values from the ACS data. Housing unit rents/prices are imperfectly correlated with land rents over space, because housing units tend to be smaller where land rents are high. The general shape of the relationships between distance and housing values is similar across MSAs to that of distance and income, but much noisier. Results are available from the authors upon request.

the pooled graph aggregates many different patterns at the MSA level, and the overall shape is heavily influenced by the larger population MSAs that have a larger number of tracts.

Disaggregating the tracts by MSA reveal that city-specific relationships between income and distance vary considerably, along multiple dimensions (Figure 2). The shape of the pooled graph – incomes initially decreasing with distance from CBD before rising again -- is mirrored in several individual MSAs (Boston, Chicago, Denver, Houston, New York, Philadelphia, and Washington) although the distance where the inflection point occurs is not consistent. Quite a few MSAs show the "traditional" pattern of incomes rising with distance to CBD, at least up to about 20 miles (Baltimore, Cincinnati, Detroit, Los Angeles, Minneapolis, Nashville, Phoenix, and St. Louis). Incomes are essentially flat with respect to distance for a number of MSAs (Atlanta, Dallas, Miami, Pittsburgh, Riverside, San Francisco, and Tampa) while only Seattle shows a consistent decline in income moving away from the CBD. Figure 2 also clearly shows variation in income levels across MSAs, similar to those shown in Table 1. Notably, the relationship between income and distance in more than half the MSAs is either non-monotonic or has large differences in slope along some portions of the graph – shapes that would be incompletely or incorrectly described by linear or quasi-linear estimations. The different relationships between income and space likely reflect a variety of underlying factors, such as concentration of employment, transportation networks, and historical residential patterns, including the tendency of similar households to co-locate. In the concluding section, we will lay out some hypotheses for the cross-MSA differences in shape that could be explored in future research.

3.2) Describing low-income neighborhoods in featured MSAs

Figure 3 shows more clearly the varying income-space relationships for four featured MSAs: Atlanta, Detroit, Los Angeles and Washington. In the graphs, the black line shows the locally smoothed regression, while individual tracts are shown in the scatterplots, colored by income quartile from red (poorest) to light gray (richest). Focusing on the regression lines, Atlanta's estimated relationship is relatively flat, Detroit and Los Angeles have upward sloping functions, and Washington's graph is non-monotonic, with a downward slope from zero to five miles, then inverting and sloping upward to about 20 miles before flattening out. Additionally, the lines show that the four MSAs differ considerably in income levels (DC has the highest average); and steepness of slope (LA's is the steepest, Atlanta's is the flattest). The scatterplots show the underlying data points that produce these estimations, and are particularly useful for showing the extent of spatial overlap between tracts in the four quartiles; this can be interpreted as the amount of income dispersion within given distance bands. For instance, looking at tracts within 10 miles of the CBD, which can be thought of as the central urban core, Atlanta and Washington have considerable income diversity, with numerous tracts from all four income quartiles represented. In Los Angeles, tracts within five miles of the CBD are almost exclusively the lowest two income quartiles, with the top two quartiles first appearing in the 5-10 mile range (driving the upward slope). Detroit shows the greatest spatial income segregation: most of the poorest tracts are within 10 miles of the CBD, the next two income quartiles span roughly 10-20 miles, and most of the highest income tracts are beyond 20 miles of the CBD.[12] The dispersion of tracts around the estimated regressions indicate the widest range of tract income in Los Angeles, with the lowest dispersion in Detroit.

[12] Graphing distance from the CBD does not take into account directional differences; these will be explored further in Figures 10-13 below.

Median income is only one possible way to identify poor tracts, and has two potential limitations. First, because the income quartiles are assigned within MSAs, "low-income" tracts may actually vary quite a bit in the prevalence of households below the poverty line. Second, using median income for the tract obscures within-tract variation in household income. To see whether these measurement issues affect the observed spatial income patterns, we construct similar graphs showing the relationship between distance to CBD and percentage of population below the federal poverty line (Figure 4).[13] The general spatial trends of poverty are largely similar across the four MSAs. Tract poverty rates decline with distance to CBD in all four MSAs, and the lowest income tracts have higher average poverty rates, as expected. Beyond that, the graphs vary widely in slopes, intercepts, and dispersion. Detroit has the most tracts with poverty rates over 60 percent, while few of Washington's tracts are over 40 percent poor. The graphs for Detroit and Los Angeles have steeper slopes, showing that poverty rates decline quite rapidly within the first 10 miles of the CBD before flattening out. Looking at the 0-10 mile range, three of the four MSAs display a wide range of tract poverty rates, meaning that centrally located neighborhoods are not universally poor. However, nearly all tracts located within 10 miles of Detroit's CBD have poverty rates above 20 percent, with an average over 40 percent. Los Angeles and Detroit have a number of high poverty, low income neighborhoods located more than 20 miles from the CBD.

Within-tract income dispersion generally decreases with distance to the CBD in all four MSAs (Figure 5). This is consistent with the ambiguous predictions of income sorting from theoretical models: while low-income households may live near the CBD because of their willingness to live at high densities, or to gain access to urban services such as public transit or

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[13] Individuals and families are determined to be below the federal poverty line based on both income and family size, so two families with the same income level may have different poverty status.

social services, some high-income households also value proximity to the CBD, perhaps to minimize commuting costs or to access social and cultural amenities. Central cities generally allow greater variation in housing density (smaller lots, taller buildings), which can accommodate a wider range of household incomes, whereas uniform lot size zoning in many suburban communities helps reinforce income homogeneity in those jurisdictions. In all four MSAs, some of the lowest-income tracts have relatively high income dispersion. Interestingly, all four cities have at least one higher income tract (top two quartiles) with relatively high levels of income dispersion, but these are outliers to the general pattern. Together, Figures 3-5 suggest that incomes are generally lower and poverty rates are higher near the CBD, but that centrally located neighborhoods contain a mix of low and high income households.

3.3) Racial/ethnic composition, income and location

As noted in the introduction, long-standing income and wealth differences across racial and ethnic groups in the U.S. suggest that neighborhood-level racial/ethnic composition will be correlated with spatial income patterns. The overall racial/ethnic composition of our 24 sample MSAs varies considerably, with cities in the Northeast and Midwest being predominately black-white, while Western and Southwestern cities have smaller black populations and larger Hispanic and Asian populations (Table 1). MSA-level differences in racial/ethnic composition are also reflected in tract-level measures for low-income neighborhoods (Table 4). For instance, the lowest-income neighborhoods in Phoenix, San Diego, Riverside, Denver and Los Angeles are, on average, less than 10 percent black, while more than 45 percent Hispanic. These trends are reversed in Baltimore, Detroit and St. Louis, where poor tracts are on average more than 70 percent black and less than 8 percent Hispanic. Although on average low-income tracts have smaller Asian populations than higher-income tracts, in three MSAs – Minneapolis, San

Francisco and Seattle – low-income neighborhoods have relatively large Asian population shares (more than 10 percent). And in a few MSAs, such as Cincinnati and Pittsburgh, low-income neighborhoods are majority non-Hispanic white.

Calculating simple correlation coefficients between distance, population density, income, and ethnicity for all 24 MSAs together confirms well-known patterns. Centrally located neighborhoods are more dense, less affluent, and have larger black and Hispanic population shares (Table 5, columns 1-5). As neighborhood income increases, population density declines, as do black and Hispanic population shares, while Asian population shares increase (columns 6-9). However, these aggregate trends mask substantial differences across MSAs. Population density gradients with respect to distance tend to be flattest among Sunbelt cities in the South and West, and steepest among Northeast and Midwest cities. Income density gradients are steepest in the Midwest and West, and flatter in the South. Although the correlation between income and percent black is negative for all MSAs, the absolute value of the correlation coefficient ranges from less than 0.3 in several Western MSAs (Los Angeles, Phoenix, and Riverside) to greater than 0.6 in Southern and Midwestern MSAs (Atlanta, Baltimore, Detroit, Minneapolis and St. Louis). The correlations between income and Hispanic and Asian population shares likewise vary substantially across MSAs, although in several MSAs, the overall population of these groups is too small to draw strong conclusions. Similarly, black population shares are strongly negatively correlated with distance to the CBD in Midwestern and Southern MSAs, but only weakly correlated with distance among most West Coast MSAs. Spatial patterns among Hispanics and Asians also vary across MSAs.

To investigate the spatial patterns of income and race for our four highlighted MSAs, we develop a set of matched graphs and maps for Atlanta, Detroit, Los Angeles and Washington.

The graphs show the locally smoothed regressions of distance to CBD and tract share of blacks, Hispanics, and Asians, overlaid with scatterplots of tracts with the colored points reflecting income quartiles in the same way as previous figures. Black population shares decline with distance from the CBD for all four MSAs, but with notably different shapes and slopes (Figure 6). Atlanta has the smoothest downward slope and the most uniform dispersion of tracts along the line; although many of the tracts nearest to the CBD have very high black concentrations, there are majority black tracts at farther distances in the MSA, and there are close-in tracts with very small black populations. The pattern in Washington, DC is somewhat similar to Atlanta, although the curve is shifted downward and to the right, with a lower average black share and the highest concentration tracts located between 5-10 miles from the CBD.[14] Detroit shows an almost bimodal pattern among tracts within 10 miles of the CBD: centrally located tracts have black populations above 70 percent or below 30 percent, with very few tracts in between. Detroit also has the sharpest drop in black population moving away from the CBD. Los Angeles has by far the lowest average black population share (6.5 percent for the MSA), and only two percent of tracts are more than 40 percent black, producing a nearly flat race-distance gradient. In all four MSAs, the lowest income tracts have an above average black population share, and this is most pronounced in Atlanta and Detroit. However, all four MSAs also have low-income tracts with very low black population shares.

The spatial patterns of ethnicity across MSAs are quite different when looking at neighborhood Hispanic population shares (Figure 7). In Los Angeles, nearly 20 percent of tracts are more than 80 percent Hispanic, while among the other three MSAs, fewer than 10 percent of

[14] The sharp dropoff around 20 miles reflects the eastern border of the MSA, formed by Prince George's County. The counties immediately east of Prince George's, Howard and Anne Arundel, also have relatively large black population share but are defined as part of the Baltimore MSA.

tracts are above 40 percent Hispanic. Los Angeles has a clearly downward sloping relationship between Hispanic population and distance to CBD. Los Angeles also has the greatest dispersion among tracts at all distances from the CBD: distance is strongly predictive of Hispanic population share, but with high variance. Atlanta and Washington have slightly parabolic graphs, with the greatest concentration Hispanic neighborhoods located between 5 and 15 miles from the CBD. In Detroit the relationship is nearly flat with a small cluster of heavily Hispanic tracts around four miles from the city center. The income scatterplot shows that most of the poorest tracts in Los Angeles are heavily Hispanic. In the other three MSAs, some of the poorest tracts are highly Hispanic, but most poor tracts are largely non-Hispanic. Los Angeles also has the greatest economic diversity among highly Hispanic tracts; of the tracts with at least 50 percent Hispanic population, 17 percent are in the top two income quartiles.

Correlations between Asian population share, location and income in these four MSAs display yet a different pattern. While highly black and Hispanic tracts tend to have below-average income and be clustered near the CBD, Asian population shares are positively correlated with income and essentially uncorrelated with distance to CBD (Table 5). The general shape of the graphs confirm mostly flat relationships between Asian population and distance (Figure 8). Tracts in Atlanta and Detroit are, on average, less than 10 percent Asian, with very few tracts above 15 percent. Most of these tracts are in the highest two income quartiles and located 20-30 miles from the CBD. Washington has more tracts that are at least 15 percent Asian, and they are also mostly affluent and suburban, but there are some poor tracts with relatively high Asian concentrations. In Los Angeles, which has the largest overall Asian population, Asian-dominated tracts are economically diverse and scattered throughout the metropolitan area. The scatterplot shows a much more dispersed pattern in LA; the most concentrated tracts are around

80 percent Asian - much higher than the other three MSAs -- and highly Asian neighborhoods are found in every income quartile and at all distances from the CBD.

3.4) Spatial clustering by income and race/ethnicity

One limitation of the previous graphs is that the spatial measure only indicates distance to CBD, but not direction; this may obscure important patterns such as north-south or east-west differences, which often occur due to physical barriers (highways, railroads, water bodies) or historical patterns of development. The maps in Figures 9-12 offer another view of spatial patterns in the four sample MSAs, showing income quartiles (within MSA) and racial and ethnic composition.[15] The Atlanta MSA – which has the most even radius from the CBD to the urban fringe - shows north-south differences in both income distribution and racial composition (Figure 9). The income map (top left quadrant) confirms and expands on the results of Figure 3; the lowest income tracts are closest to the CBD, particularly on the south side, with income rising in the farther suburbs. Income rises more rapidly moving north from the CBD than in the other three directions. Mapping percent black (top right quadrant) shows considerable overlap south of the CBD between the lowest income tracts and those with the highest black population shares. About 17 percent of Atlanta's tracts are more than 75 percent black, and another 13 percent are between 50-75 percent black. As shown in the bottom two quadrants, the most heavily Hispanic and Asian tracts – which are mostly 25-50 percent Hispanic or Asian -- are located in the northeast part of the MSA, not directly adjacent to the CBD.

[15] Because the MSA-level racial/ethnic composition varies widely across the four MSAs, it is difficult to pick consistent cutoff values for the categories that will be equally visible within and across MSAs. Our goal is to allow straightforward comparisons of spatial concentration across racial/ethnic groups within an MSA, as well as some comparison across the four MSAs, so we opt for constant percentile cutoffs (25^{th}, 50^{th} and 75^{th} percentiles). Not all MSAs will have tracts in the top two percentile buckets for all racial/ethnic groups.

The maps of Detroit similarly show substantial overlap immediately north of the CBD between lowest-income tracts and highest black concentrations (Figure 10). Unlike Atlanta's even radial pattern outward from the CBD, the Detroit MSA is truncated just southwest of the CBD due to Lake Erie and the US-Canadian border, so it is not possible to observe tracts at similar distances in all directions. Although central tracts are mostly low income, a few higher-income tracts are located a short distance west of the CBD and surrounded by much lower-income tracts; these correspond to a few incorporated townships within Wayne County. The most concentrated black tracts (more than 75 percent black) are also located near the CBD and to the immediate east/northeast, in an area almost perfectly matching the Detroit city boundaries (top right quadrant). The most heavily Hispanic tracts (about 1.5 percent of tracts are majority Hispanic) are clustered immediately west/southwest of the CBD, and are mostly low income (bottom left). The highest concentration Asian tracts (25-50 percent) are either northwest or west from the CBD, and not immediately adjacent to downtown. As with the maps of Atlanta, the Detroit maps show separation of racial and ethnic neighborhoods not merely by distance from CBD, but in different directions.

The spatial distribution of income in the Los Angeles metro area roughly follows the traditional monocentric model of land rents, despite LA having highly dispersed and polycentric employment patterns (Figure 11, top left). The lowest-income tracts are closely clustered within central LA, near Downtown Los Angeles and to the south/southeast of the CBD. Income increases moving away from the CBD in all directions. There is also some spatial correlation between the lowest-income neighborhoods and black population shares (top right); majority black tracts are located throughout South LA and to the southwest of downtown, although a few affluent black tracts are located north of the CBD in the cities of Palmdale and Lancaster.

Clusters of heavily Hispanic tracts are located around the CBD and scattered across the MSA (bottom left), with large concentrations south of Downtown, East in the San Gabriel Valley and extending towards Riverside County, as well as northwest in the San Fernando Valley, and southeast in the cities of Anaheim and Santa Ana. Comparing the top and bottom left maps shows that majority Hispanic tracts in Los Angeles overlap substantially with low-income tracts. Clusters of majority Asian tracts are also found across the LA metro area (bottom right), including east of the Downtown in the San Gabriel Valley, just west of the CBD (Koreatown), as well as dispersed throughout Orange County and the West Side of Los Angeles. Some heavily Asian clusters overlap with low-income tracts, but others overlap higher income areas.

Income and racial patterns in the Washington metropolitan area are asymmetrical relative to the CBD and show substantial racial separation (Figure 12). Low-income tracts in the Washington metro area are mostly clustered in the eastern half of the District of Columbia and the closer-in tracts in Prince George's County, Maryland, just east of DC (top left). However, a string of low-income tracts extends southwest of the CBD in the relatively distant exurbs (Stafford and Spotsylvania Counties, Virginia), and northwest of the DC in Frederick County, Maryland. In general, tract income rises moving west/northwest of the CBD. Confirming the results of Figure 6, there is a strong spatial correlation between lower-income tracts and those with the largest black population share (top right). Majority black tracts are almost exclusively located in the eastern half of the MSA, in DC and Prince George's County, although tracts with 25-50 percent black population shares are also found in the southern Virginia suburbs. In contrast, clusters of Hispanic and Asian tracts are dispersed throughout the MSA. Hispanic tract clusters are located in DC north of the CBD, and in several of the suburban counties in every direction – a relatively dispersed pattern, not strongly correlated with income. Majority Asian tract clusters are found just north of the CBD and across suburban counties, overlapping some of the highest income tracts in Fairfax County, Virginia and Montgomery County, Maryland. As in Los Angeles, Asian households in the DC metro area include both recent immigrants and native-born households from several generations, and are diverse in national origin and income.

The second approach to measure tract clustering, the correlation between a tract's own characteristics and the characteristics of its spatially near neighbors, is shown in Table 6. The correlation coefficients were calculated for tracts in all MSAs pooled and for tracts in each of the four featured MSAs separately. Results indicate a high degree of clustering among tracts by income (0.81 for all MSAs) and race/ethnicity, with particularly strong clustering by percent black (0.93 for each separate MSA and the pooled sample). These patterns are generally consistent across the four MSAs, with a few differences. Income correlations are strongest among tracts in Detroit and Los Angeles, and weakest in Washington, DC. Correlation of percent black is at least 0.9 in all four MSAs. Of the four featured MSAs, Los Angeles has the strongest correlation between neighbors in Hispanic and Asian population shares. The correlations in Washington confirm visual patterns from the maps: black tracts are highly concentrated, Asian tracts are also clustered but less strongly than black tracts, while Hispanic neighborhoods are the most dispersed. Very similar results are obtained when estimating correlations by income quartile and at different distance bands from the CBD, suggesting that income and racial clustering is similarly prevalent among suburban tracts as within central cities.

The final measure of racial/ethnic concentration is shown in Figure 13: the share of each MSA's total population and population by racial/ethnic group living within certain distances of the CBD. Like the neighboring tract correlations in Table 6, this approach can be consistently interpreted across MSAs with widely varying overall racial/ethnic compositions. We divide tracts into three distance bands: the central urban core (0-10 miles), inner ring suburbs (10-20 miles), and outer ring suburbs (more than 20 miles). We then aggregate the share of MSA total population, black, Hispanic and Asian populations living within each ring. Across the four MSAs, Washington has the most centralized population (about 40 percent within 10 miles) and Atlanta's population is least centralized (less than 20 percent within 10 miles, nearly 50 percent beyond 20 miles). Comparing the three ethnic groups, blacks are most likely to live within the urban core in all four MSAs, and Asians are most likely to live in the outer ring suburbs, though the size of differences vary across cities. Atlanta has the smallest differences in degree of centralization across all three ethnic groups (top left). Blacks are slightly more concentrated in the central core, and blacks and Hispanics are slightly more concentrated in the inner suburban ring, but the difference between overall population share and ethnic group share is less than 10 percentage points for nearly all groups and distance bands. Detroit has the largest discrepancy between black population shares and overall population: more than half of Detroit's black residents live in the urban core, compared to 23 percent of the overall population, while only 12 percent of blacks live beyond 20 miles of the CBD, compared to 35 percent of the MSA overall. Hispanics in Detroit are also substantially concentrated in the central core (40 percent), while Asians are more concentrated in the outer ring suburbs (50 percent). Los Angeles also has substantial concentration of blacks within the central core (48 percent of blacks, compared to 28 percent of the MSA population), while Hispanics and Asians are distributed similarly to the overall population. In Washington, blacks are more likely to live in the central core (54 percent compared to 40 percent), Asians are more likely to live in inner ring suburbs (45 percent compared to 34 percent), while Hispanics are roughly proportionally distributed across the three distance bands. Overall, Figure 13 confirms visual analysis of the previous maps and graphs:

racial/ethnic clustering near the CBD is substantially more prevalent for blacks than Hispanics or Asians, regardless of the overall MSA racial/ethnic composition.

4) Discussion

This paper explores spatial patterns of neighborhood income and race/ethnicity for U.S. metropolitan areas, focusing particularly on whether centrally located neighborhoods are lower income and have larger non-white populations. Results suggest that, on average, income increases with distance to the CBD, while black and Hispanic population shares decline. However, spatial income and racial/ethnic patterns vary widely within and across metropolitan areas. Not all centrally located neighborhoods are low-income or non-white, and many low-income or non-white neighborhoods are located at some distance from city centers. Analysis of income-distance correlations for a set of 24 large MSAs suggests three frequent patterns: income rising with distance to CBD, income uncorrelated with distance (flat), and a non-monotonic relationship with local maxima adjacent to the CBD and again further out. The relationship between racial/ethnic composition and distance from CBD is more complex, varying across MSA and across groups within MSAs. In general, black residents are more likely than Hispanics and Asians to be concentrated near the CBD, while Asians are more likely to live in inner- or outer-ring suburbs. Spatial concentration of non-white neighborhoods is more prevalent than clustering of low-income neighborhoods. By presenting findings both for a large set of MSAs and more detailed findings for a few cities, our results illustrate the considerable diversity in spatial patterns across MSAs.

The analysis presented in this paper is purely descriptive, intended to document the existence of varying spatial patterns, although the results naturally raise questions about the reasons behind cross-MSA differences. Drawing on the descriptive results and prior literature on neighborhood sorting, we can suggest several factors that may contribute to these differences, which would benefit from further investigation. If income sorting is driven by variation in land values, then cross-city differences in urban spatial structure and transportation costs are likely to be important. Specific factors could include the degree of employment centralization, number and size of employment centers, location of transportation networks, and the presence of location-specific natural and cultural amenities. Households also sort based on spatial patterns in the quality and density of housing stock, which reflects both land values and locally determined policies (zoning and building codes). The pronounced and idiosyncratic patterns of ethnic clustering raise questions about historical development patterns within several of these cities, which could be tested using lagged neighborhood ethnic composition. For instance, why is DC's black population primarily on the eastern side of the city and its adjacent suburbs, while Atlanta's is concentrated south of the CBD? What role is played by historical or ongoing immigrant gateway neighborhoods? Some of these questions could be investigated with relatively large samples of MSAs, but some will likely require more focused analysis of individual cities that can account for locally-specific institutions and histories.

In addition to exploring the reasons behind cross-MSA spatial patterns, our results suggest several areas for future research. How persistent are patterns over time? Some of the cities we examine have seen gentrification of centrally located neighborhoods over the past 20 years – e.g., among the featured MSAs, Washington, DC and Los Angeles in particular. How has gentrification changed the overall MSA patterns of income and race? Detroit and other

Midwest cities have declined in population size over many decades; do these MSAs have consistently different income-racial-spatial patterns than MSAs with growing populations? How does the growth of particular ethnic groups, notably Hispanics, change the overall racial distribution and neighborhood evolution? How do in- and out-migration patterns by various ethnic groups contribute to overall spatial patterns? Finally, how correlated are neighborhood income and racial composition with broader measures of economic well-being, such as wealth creation and retention, employment outcomes, housing quality and affordability, and health outcomes? Are ethnic or income spatial patterns correlated with MSA-level industrial composition? Are there consistent differences between low-income urban neighborhoods and low-income suburban neighborhoods in economic opportunity or quality of life?

The spatial patterns of income and race have several practical policy implications, particularly for spatially targeted economic development or poverty alleviation efforts. Programs such as Community Development Block Grants (CDBG), Low Income Housing Tax Credits (LIHTC), and New Markets Tax Credits are intended to channel funding into distressed areas for affordable housing, job training, support for entrepreneurs and small businesses, and other community and economic development goals. The geographic definitions used to determine program eligibility vary by program; for instance, CBDG funds are allocated to states and large local governments, with considerable discretion on where (and how) they are used within jurisdictions, while LIHTC projects have usage guidelines by census tract status. Our results suggest that the geographic level and definition of targeting will have different implications for reaching poor households. Large cities and urban counties certainly contain many poor neighborhoods and a sizeable share of the nation's low-income households, but many lower-income and minority households and neighborhoods are located outside of these political jurisdictions. In particular, lower income and minority neighborhoods that are outside incorporated cities (i.e. unincorporated county areas) may be less visible than urban constituencies with similar economic need.

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Table 1: Sample metropolitan areas

MSA	Census division	Pop (mi)	Median income	Income, Q1	Black	Hispanic	Asian	# tracts
Atlanta	South Atlantic	4.9	65,769	44,536	32.7	5.3	10.6	839
Baltimore	South Atlantic	2.3	77,264	52,242	28.9	5.1	5.1	573
Boston	New England	4.3	94,863	65,688	6.9	6.9	9.9	913
Chicago	East North Central	8.4	70,398	46,175	16.7	5.9	21.5	2,005
Cincinnati	East North Central	1.9	64,797	43,809	12.4	2.2	2.9	451
Dallas	West South Central	5.4	62,660	40,864	15.0	5.8	28.2	1,061
Denver	Mountain	2.5	77,688	52,863	5.2	3.9	22.6	583
Detroit	East North Central	3.8	59,728	35,739	22.8	3.8	4.1	1,139
Houston	West South Central	5.4	58,167	40,500	16.8	7.1	36.2	924
Los Angeles	Pacific	12.0	62,253	42,151	6.5	15.1	44.9	2,716
Miami	South Atlantic	4.3	51,910	37,500	20.2	2.3	42.7	848
Minneapolis	West North Central	3.0	81,848	62,875	7.4	6.2	5.4	707
Nashville	East South Central	1.1	64,196	44,244	14.5	2.1	6.8	244
New York	Mid Atlantic	17.0	74,853	48,333	15.8	10.3	23.6	3,987
Philadelphia	Mid Atlantic	5.8	79,208	54,131	20.4	5.3	8.7	1,413
Phoenix	Mountain	4.1	62,283	43,621	5.0	3.5	29.9	920
Pittsburgh	Mid Atlantic	2.1	64,847	49,688	8.4	2.0	1.5	620
Riverside	Pacific	3.7	57,987	44,145	7.1	6.2	48.9	653
San Diego	Pacific	3.1	76,266	51,625	18.0	2.3	2.8	604
San Francisco	Pacific	3.4	97,944	65,375	4.7	11.2	32.9	753
Seattle	Pacific	3.4	84,063	64,205	7.7	24.0	21.9	692
St. Louis	West North Central	2.4	68,338	46,208	5.4	12.1	9.5	531
Tampa	South Atlantic	2.7	56,098	42,397	11.4	3.2	17.3	680
Washington	South Atlantic	4.9	108,136	73,547	25.4	9.7	14.9	1,130
All MSAs		4.7	70,975	46,208				24986

Source: United States Census Bureau/American FactFinder. Population and race/ethnicity from "B03002 : Hispanic or Latino Origin By Race." Income from "S1901 : Income in the Past 12 Months (in 2014 Inflation-Adjusted Dollars)." *2010 – 2014 American Community Survey*. U.S. Census Bureau's American Community Survey Office, 2014. Web. November 2016 http://factfinder2.census.gov. Columns for median income and racial/ethnic composition are the mean tract values for the MSA. Income Q1 is the cutoff value for tracts in MSA bottom income quartile.

Table 2: Variable definitions

Variable name	Definition
distance CBD	miles to CBD
pop	total population
pop density	population/sq mi
income	Median HH income
poor	% population below federal poverty line
Gini	Gini coefficient (within-tract)
white	% non-Hispanic white
black	% non-Hispanic black
asian	% non-Hispanic Asian
hispanic	% Hispanic (all races)

Sources: United States Census Bureau / American FactFinder. Gini from "B19083 : Gini Index of Income Inequality." Income, population, and race/ethnicity from "B1701 : Poverty Status in the Past 12 Months." Population density from "GCT-PH1: Population, Housing Units, Area, and Density: 2010." *2010 – 2014 American Community Survey*. U.S. Census Bureau's American Community Survey Office, 2014. Web. November 2016 - January 2017 http://factfinder2.census.gov.

Table 3: Location, income and race/ethnicity for low-income tracts (pooled)

Variable	All tracts	Low income	Non low-income	Low-income - non
distcbd	14.8	10.5	16.2	-5.7 ***
pop	4,482	4,085	4,613	-527 ***
popdens	11,313	18,685	8,881	9,804 ***
medinc	77,889	36,391	91,695	-55,304 ***
poverty	15.6	32.0	10.2	21.8 ***
Gini	0.42	0.45	0.41	0.04 ***
black	17.0	33.4	11.6	21.9 ***
asian	8.1	5.9	8.8	-2.9 ***
hispanic	22.5	36.4	17.9	18.5 ***
n =	24,986	6,198	18,788	

Notes: United States Census Bureau / American FactFinder. Gini from "B19083 : Gini Index of Income Inequality." Income, population, and race/ethnicity from "B1701 : Poverty Status in the Past 12 Months." Population density from "GCT-PH1: Population, Housing Units, Area, and Density: 2010." *2010 – 2014 American Community Survey*. U.S. Census Bureau's American Community Survey Office, 2014. Web. November 2016 - January 2017 http://factfinder2.census.gov. Last column shows difference in means tests between lowest-quartile tracts and top three quartile tracts, pooling across 24 MSAs. *, **, *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 4: Income, race/ethnicity and location of low-income tracts, by MSA

MSA	dist CBD	Pop dens	Income	Poverty	black	hispanic	asian
Atlanta	11.7	3,817	32,690	33.8	61.7	16.9	3.7
Baltimore	3.4	11,920	38,022	29.8	72.8	5.1	1.6
Boston	10.8	18,318	45,534	25.2	19.6	28.7	9.0
Chicago	12.0	13,703	33,482	35.4	54.8	31.7	2.3
Cincinnati	8.7	5,218	29,542	40.7	38.7	4.2	1.0
Dallas	14.1	6,462	31,951	33.5	27.6	51.8	2.5
Denver	6.5	6,985	41,849	25.8	9.6	46.0	3.1
Detroit	8.1	5,499	26,449	44.8	70.5	7.3	1.7
Houston	9.9	6,759	31,281	35.3	27.5	58.9	3.4
LosAngeles	10.2	22,405	33,352	33.4	9.7	71.0	9.6
Miami	14.4	11,166	29,830	33.7	34.5	51.8	1.0
Minneapolis	7.0	7,328	45,819	27.6	22.3	12.3	11.2
Nashville	7.1	3,637	32,516	34.8	45.7	13.3	2.3
New York	9.5	56,446	35,647	32.5	31.4	43.7	8.5
Philadelphia	8.6	16,961	37,412	32.1	52.7	16.3	4.7
Phoenix	9.3	7,344	32,185	37.3	6.8	56.9	2.0
Pittsburgh	10.1	5,676	36,453	30.4	36.3	2.1	1.5
Riverside	16.1	6,202	35,484	32.3	8.9	63.0	3.2
San Diego	12.4	12,596	39,084	27.4	7.4	57.4	8.1
San Francisco	10.6	23,353	46,142	24.6	17.7	33.4	23.7
Seattle	20.4	6,072	49,592	22.3	11.3	16.6	12.4
St. Louis	7.1	4,205	31,852	35.7	70.1	3.3	1.1
Tampa	14.6	4,459	34,117	30.0	24.1	22.9	1.9
Washington	9.4	11,928	54,588	18.4	53.6	23.2	5.5
Low income	10.5	18,685	36,391	32.0	33.4	36.4	5.9
All tracts	14.8	11,313	77,889	15.6	17.0	22.5	8.1

Notes: United States Census Bureau / American FactFinder. Poverty, population, and race/ethnicity from "B1701 : Poverty Status in the Past 12 Months." Population density from "GCT-PH1: Population, Housing Units, Area, and Density: 2010." *2010 – 2014 American Community Survey*. U.S. Census Bureau's American Community Survey Office, 2014. Web. November - December 2016 http://factfinder2.census.gov. Except for the "All tracts" row, numbers are the mean values for tracts in the lowest income quartile by MSA.

Table 5: Correlation between income, location and race/ethnicity

MSA	Distance to CBD and:					Income and:			
	Pop density	Income	Black	Hispanic	Asian	Pop density	Black	Hispanic	Asian
Atlanta	-0.54	0.12	-0.46	0.01	0.03	-0.12	-0.62	-0.31	0.20
Baltimore	-0.53	0.57	-0.48	0.04	0.15	-0.49	-0.66	-0.10	0.38
Boston	-0.56	0.07	-0.29	-0.14	-0.32	-0.29	-0.43	-0.55	-0.03
Chicago	-0.45	0.16	-0.24	-0.13	0.00	-0.07	-0.51	-0.38	0.24
Cincinnati	-0.48	0.18	-0.38	0.00	0.06	-0.41	-0.53	-0.19	0.34
Dallas	-0.32	0.11	-0.20	-0.22	0.00	-0.24	-0.40	-0.64	0.31
Denver	-0.50	0.35	-0.18	-0.35	0.11	-0.37	-0.34	-0.69	0.08
Detroit	-0.58	0.57	-0.57	-0.11	0.17	-0.42	-0.61	-0.15	0.32
Houston	-0.36	0.13	-0.18	-0.27	0.05	-0.18	-0.38	-0.62	0.32
Los Angeles	-0.41	0.35	-0.22	-0.26	0.06	-0.51	-0.20	-0.70	0.14
Miami	-0.35	0.09	0.19	-0.64	0.20	-0.19	-0.36	-0.18	0.30
Minneapolis	-0.62	0.25	-0.45	-0.30	-0.22	-0.44	-0.62	-0.49	-0.33
Nashville	-0.51	0.14	-0.47	-0.15	-0.11	-0.35	-0.57	-0.41	0.15
New York	-0.57	0.36	-0.19	-0.21	-0.13	-0.34	-0.37	-0.55	0.03
Philadelphia	-0.57	0.28	-0.35	-0.13	-0.15	-0.45	-0.60	-0.40	0.09
Phoenix	-0.40	0.33	-0.33	-0.51	0.02	-0.50	-0.30	-0.64	0.32
Pittsburgh	-0.50	0.00	-0.36	-0.22	-0.27	-0.20	-0.53	-0.02	0.30
Riverside	-0.32	0.04	-0.13	-0.44	-0.03	-0.30	-0.14	-0.59	0.51
San Diego	-0.34	0.08	-0.34	-0.07	-0.13	-0.52	-0.38	-0.70	0.15
San Francisco	-0.52	0.17	-0.13	0.13	-0.05	-0.31	-0.48	-0.54	-0.10
Seattle	-0.48	-0.37	-0.09	0.13	-0.46	-0.06	-0.52	-0.59	0.02
St. Louis	-0.49	0.41	-0.56	-0.08	-0.03	-0.23	-0.65	-0.07	0.33
Tampa	-0.28	-0.03	-0.36	-0.47	-0.15	-0.22	-0.39	-0.27	0.18
Washington	-0.47	0.14	-0.32	0.04	0.27	-0.23	-0.57	-0.41	0.23
All 24 MSAs	-0.34	0.18	-0.23	-0.12	-0.04	-0.16	-0.38	-0.43	0.16

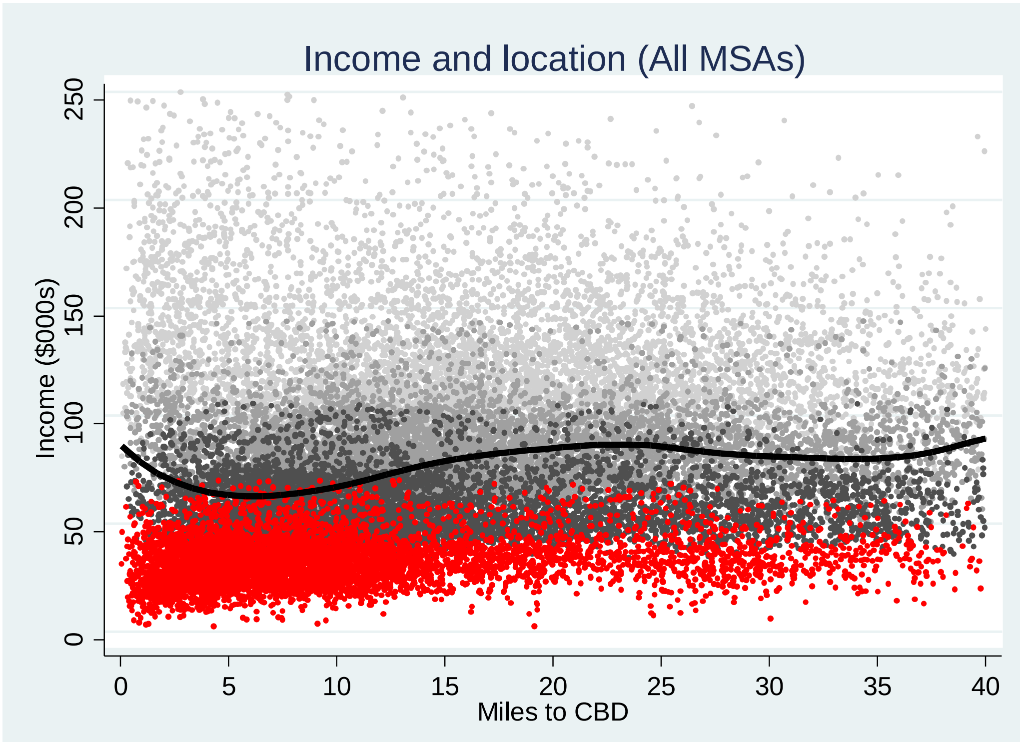
Notes: United States Census Bureau / American FactFinder. "Public Use Microdata Sample (PUMS)." *2010 – 2014 American Community Survey*. U.S. Census Bureau's American Community Survey Office, 2014. Web. 23 May 2016 http://factfinder2.census.gov.

Table 6: Comparing tract income and race/ethnicity to spatially adjacent tracts

	Income	Black	Hispanic	Asian
Atlanta	0.79	0.93	0.76	0.74
Detroit	0.85	0.95	0.88	0.73
Los Angeles	0.83	0.90	0.92	0.89
Washington DC	0.71	0.94	0.74	0.81
All MSAs	0.81	0.93	0.93	0.87

Note: Correlation coefficients between own tract's income (race/ethnicity) the distance-weighted average income (race/ethnicity) of five spatially nearest tracts.

Figure 1 Income and location (pooled MSAs)



Note: Dots are colored by income quartile (red = lowest, light grey = highest).

Figure 2 Income and location by MSA

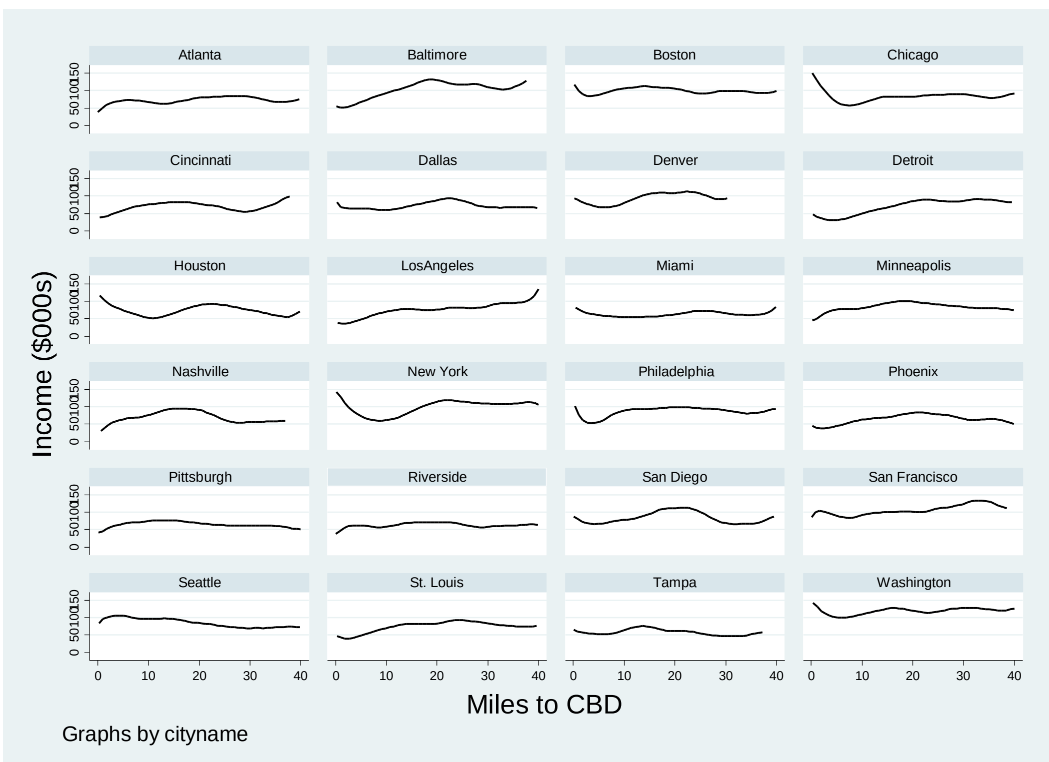


Figure 3) Neighborhood income and distance from CBD, selected MSAs

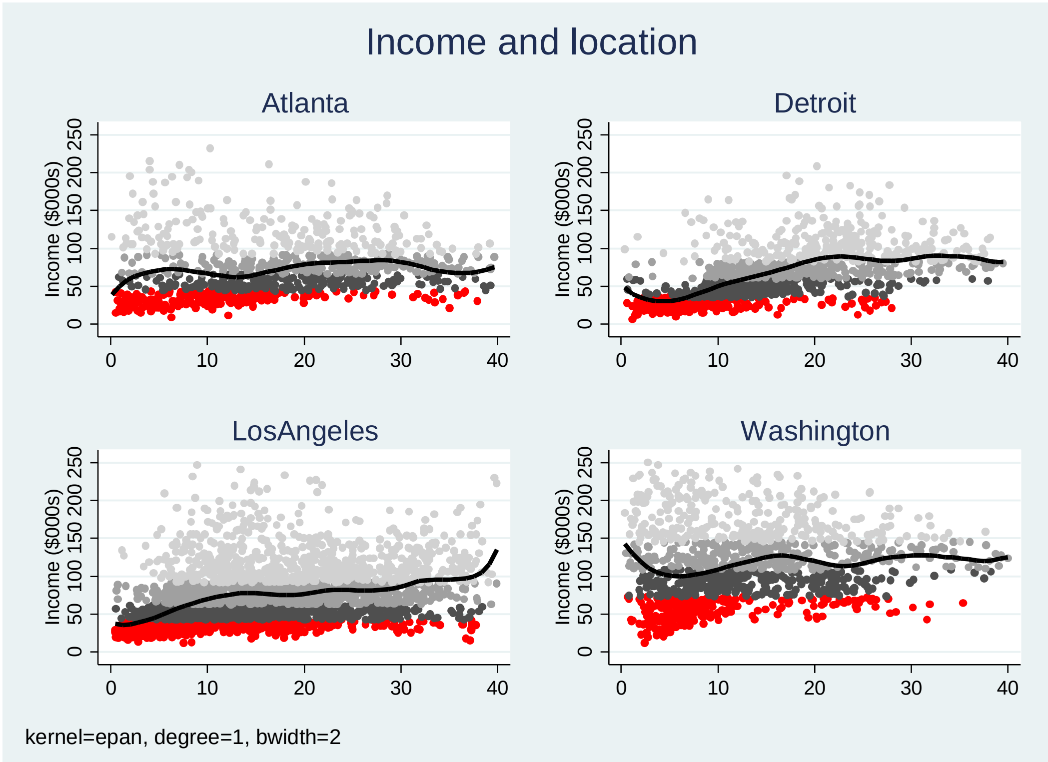


Figure 4) Neighborhood poverty and distance from CBD, selected MSAs

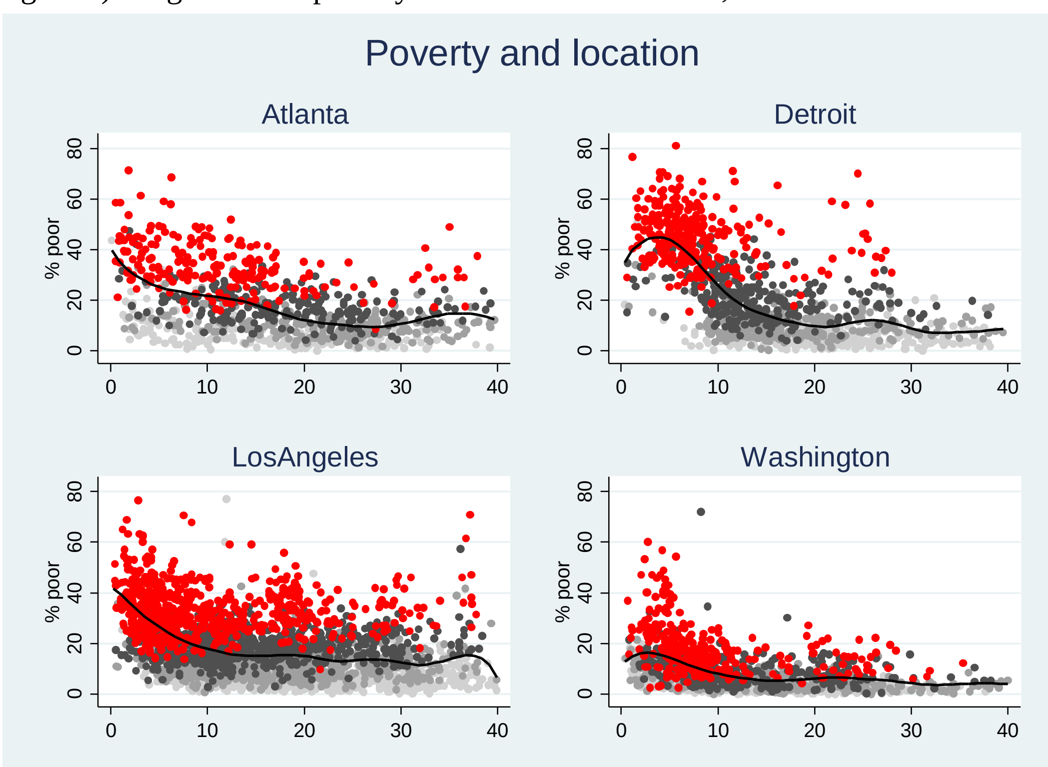


Figure 5) Neighborhood income dispersion and distance from CBD, selected MSAs

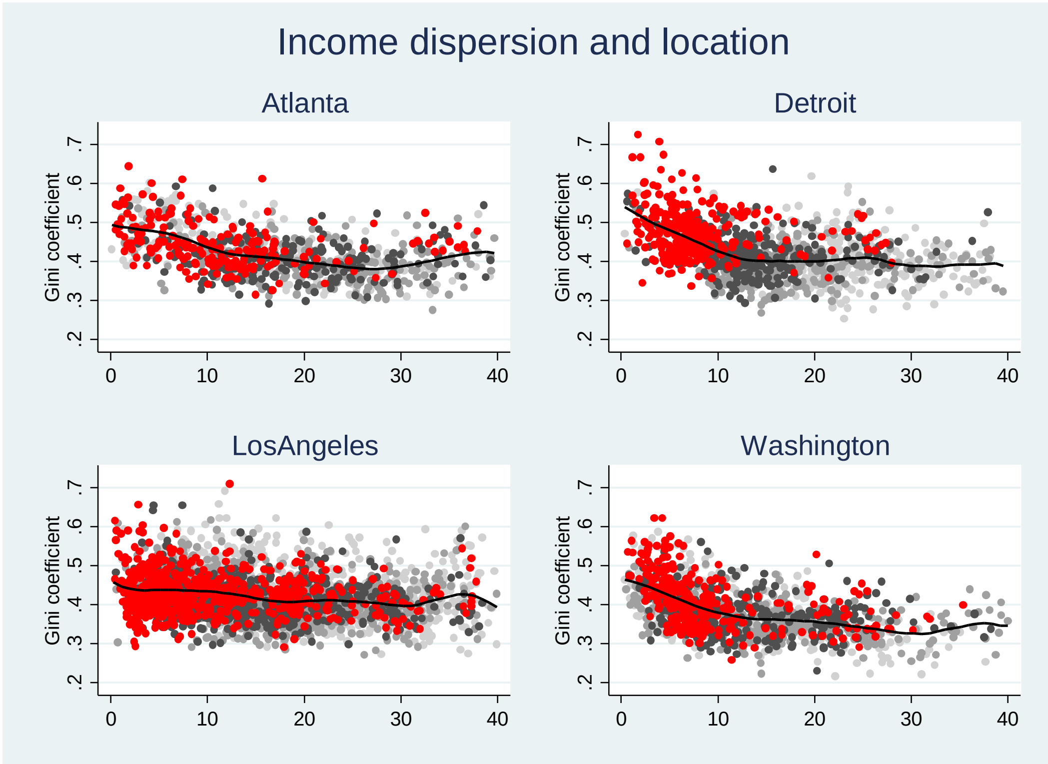


Figure 6) Neighborhood racial composition and distance from CBD: Black population

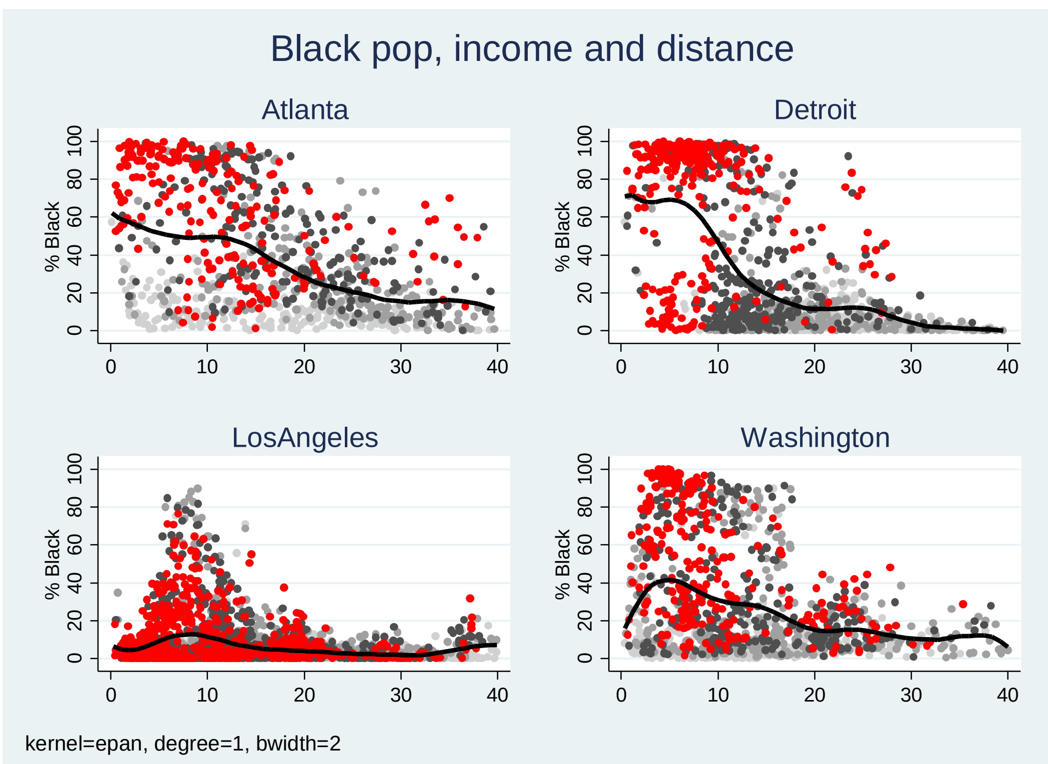


Figure 7) Neighborhood racial composition and distance from CBD: Hispanic population

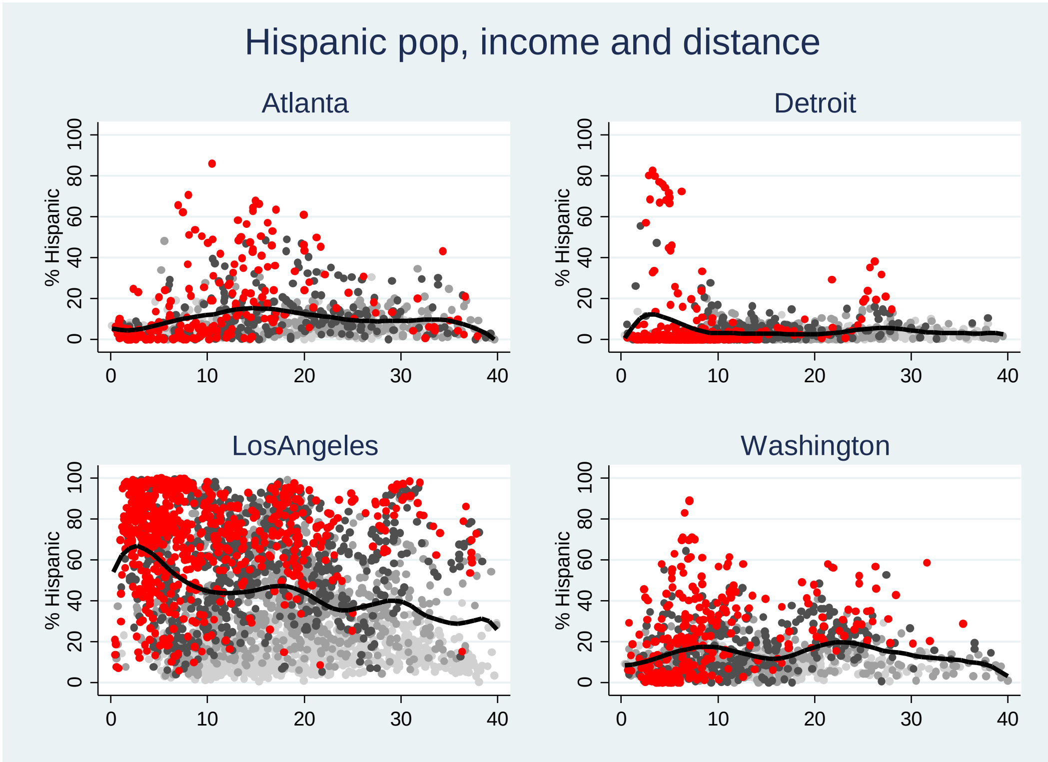


Figure 8) Neighborhood racial composition and distance from CBD: Asian population

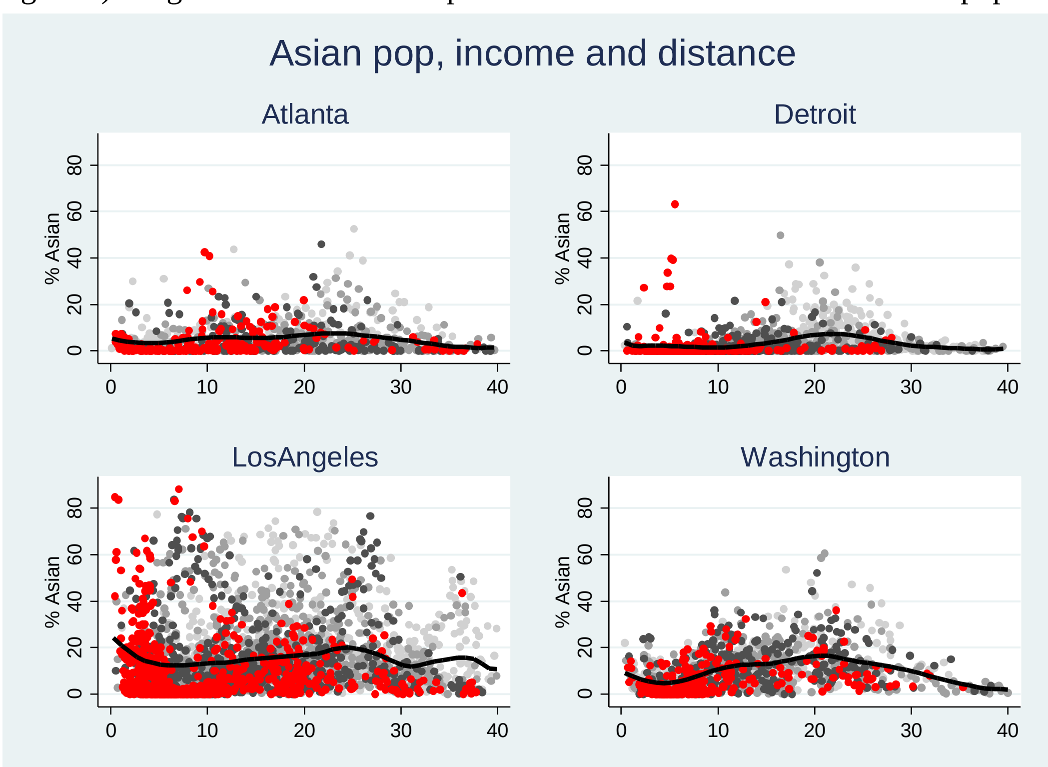


Figure 9: Neighborhood clustering by income and ethnicity (Atlanta)

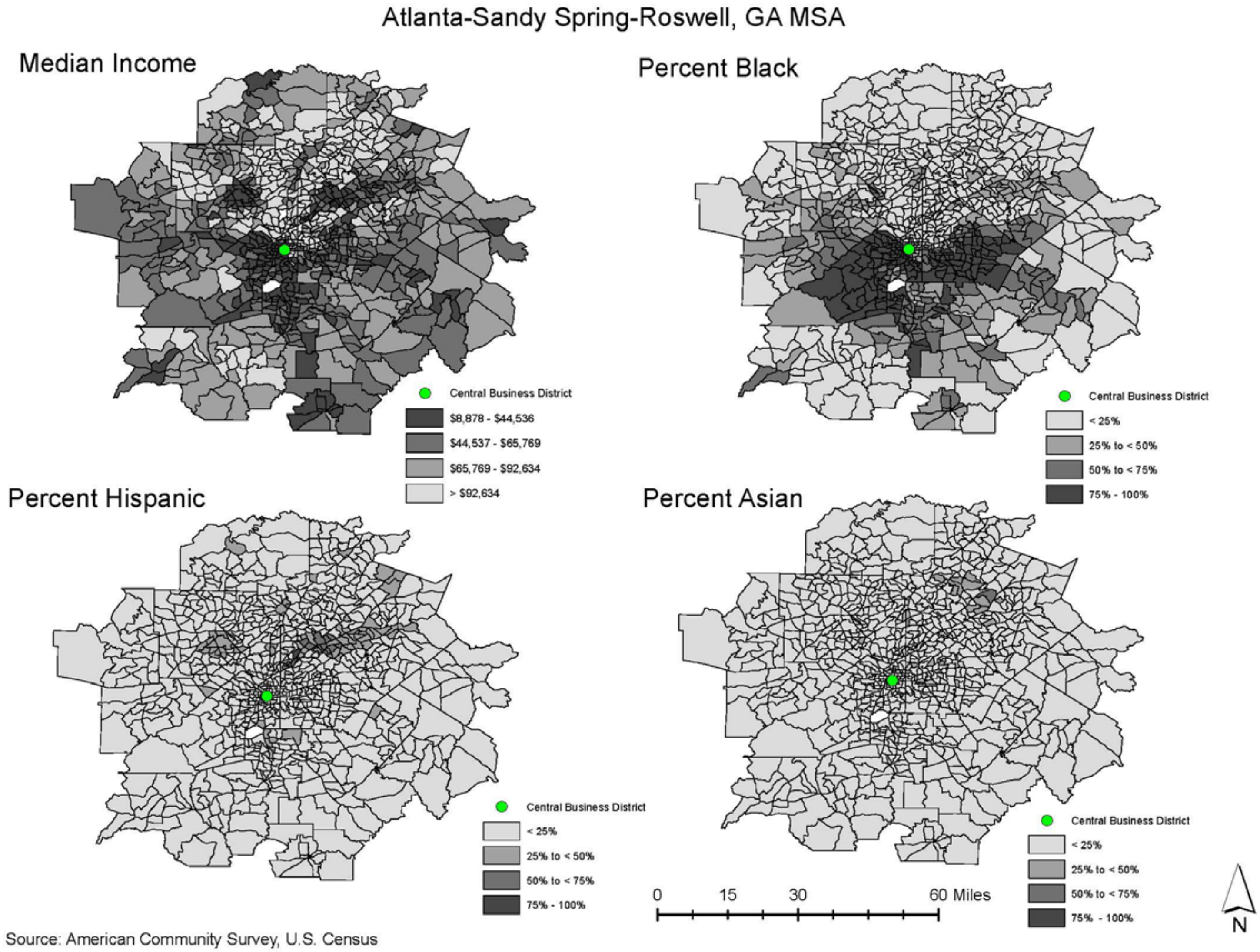


Figure 10: Neighborhood clustering by income and ethnicity (Detroit)

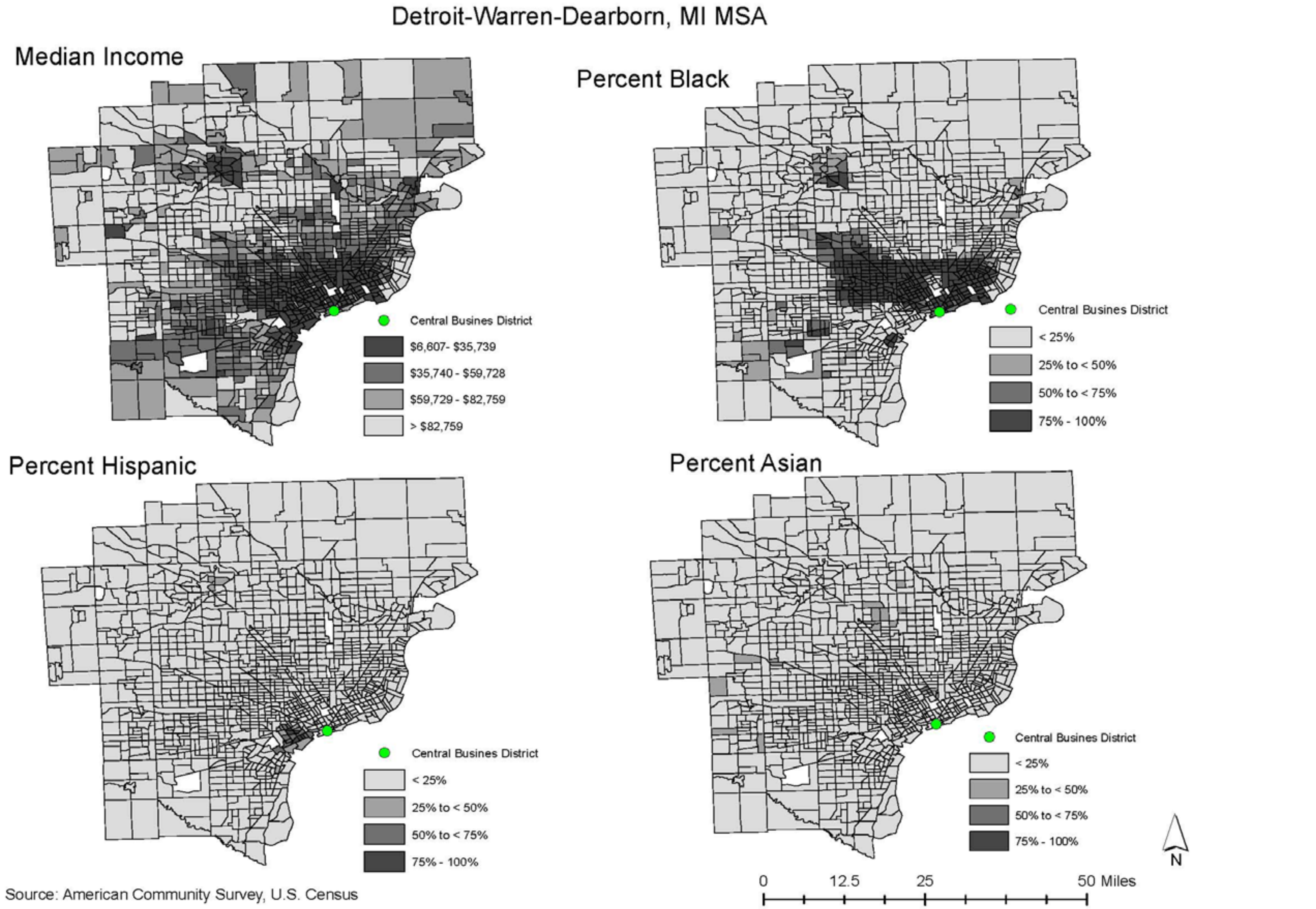


Figure 11: Neighborhood clustering by income and ethnicity (Los Angeles)

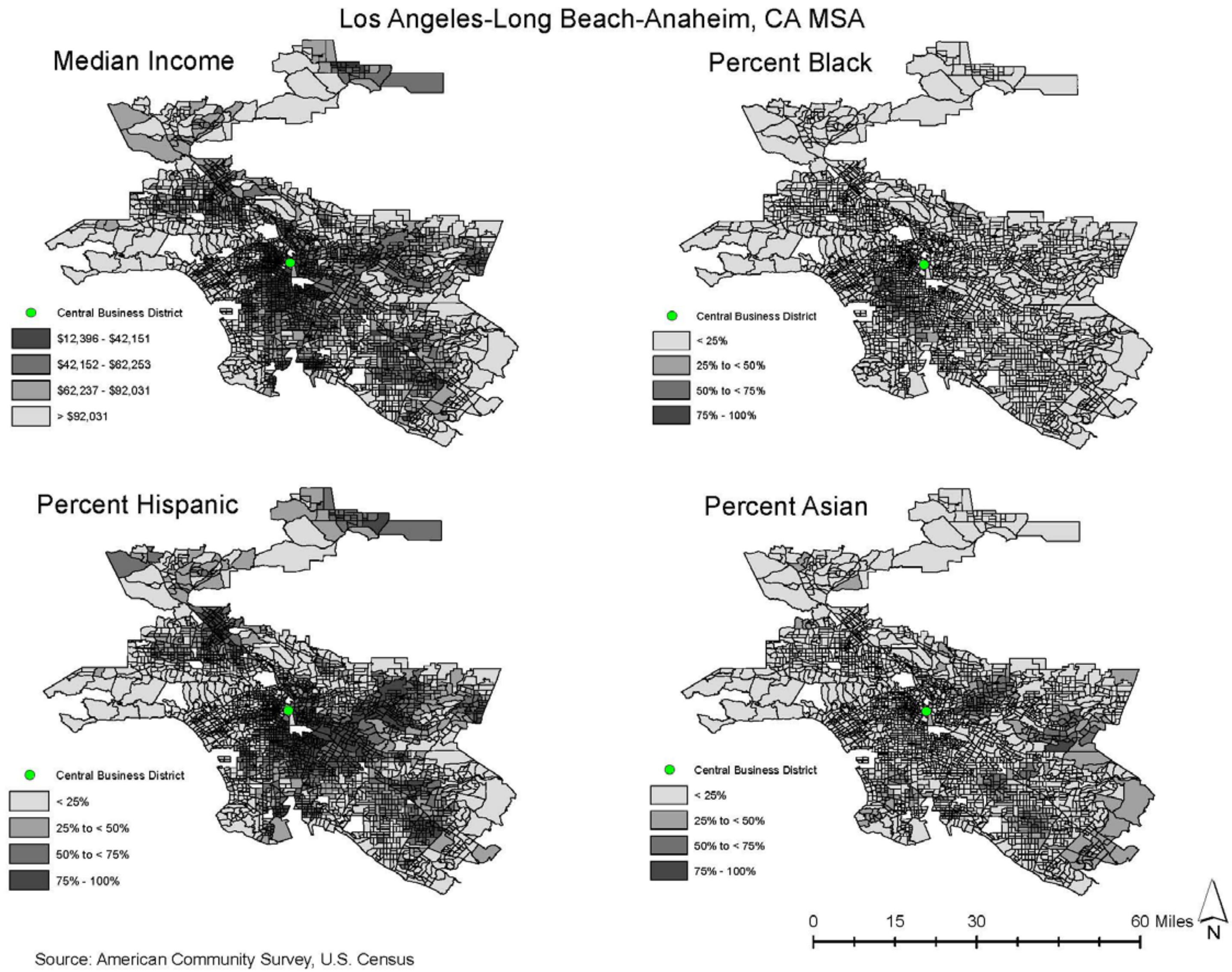


Figure 12: Neighborhood clustering by income and ethnicity (Washington DC)

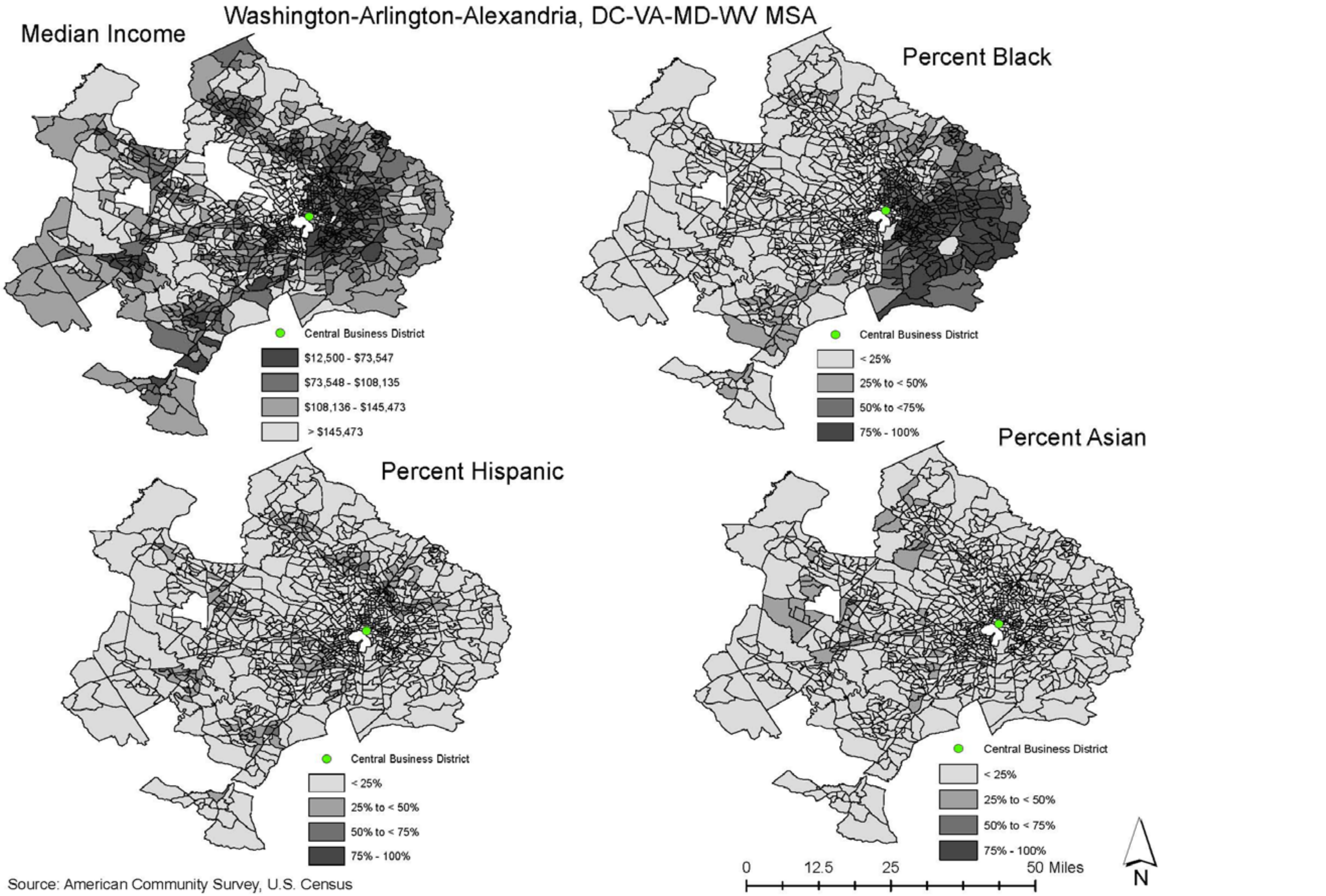
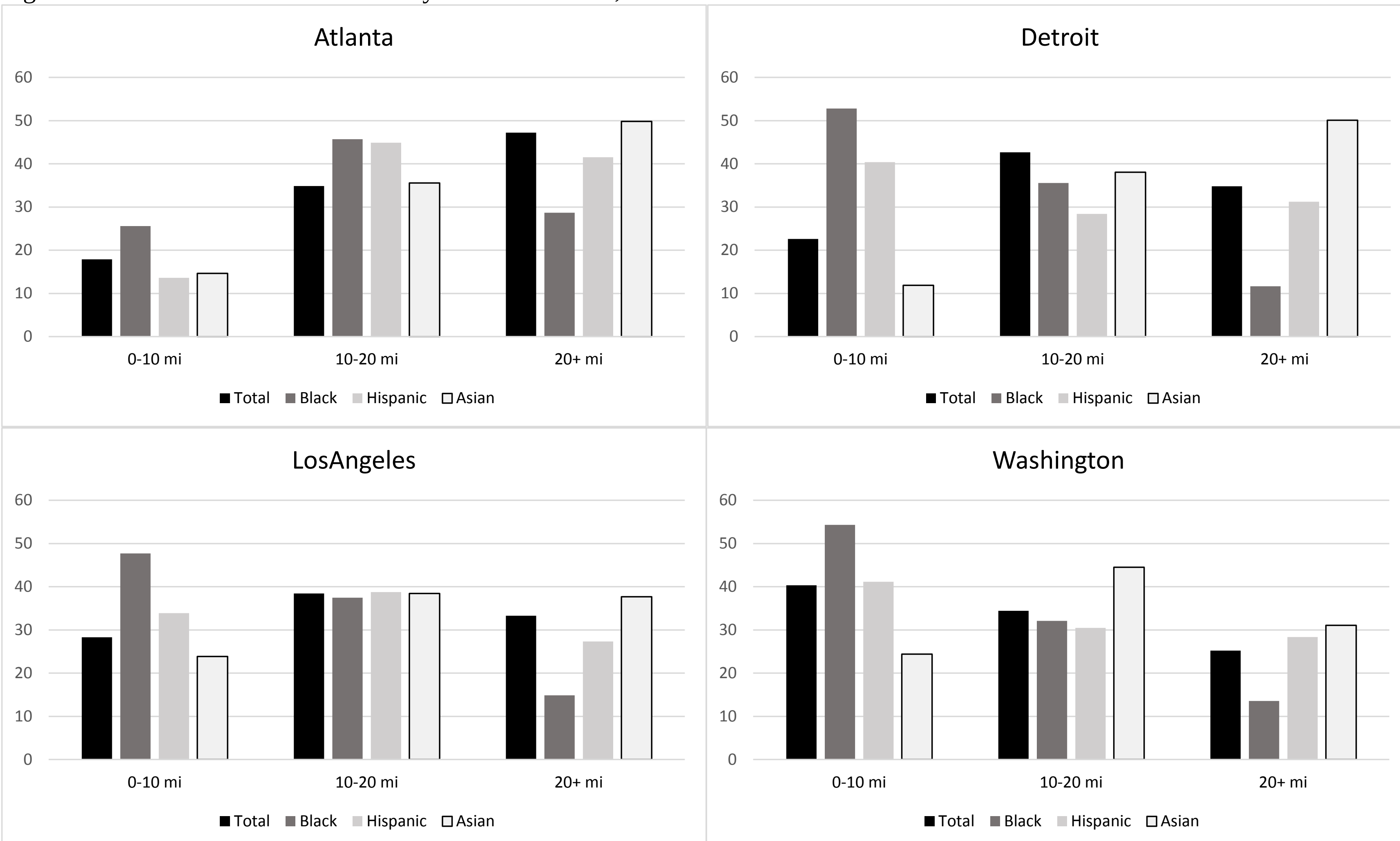
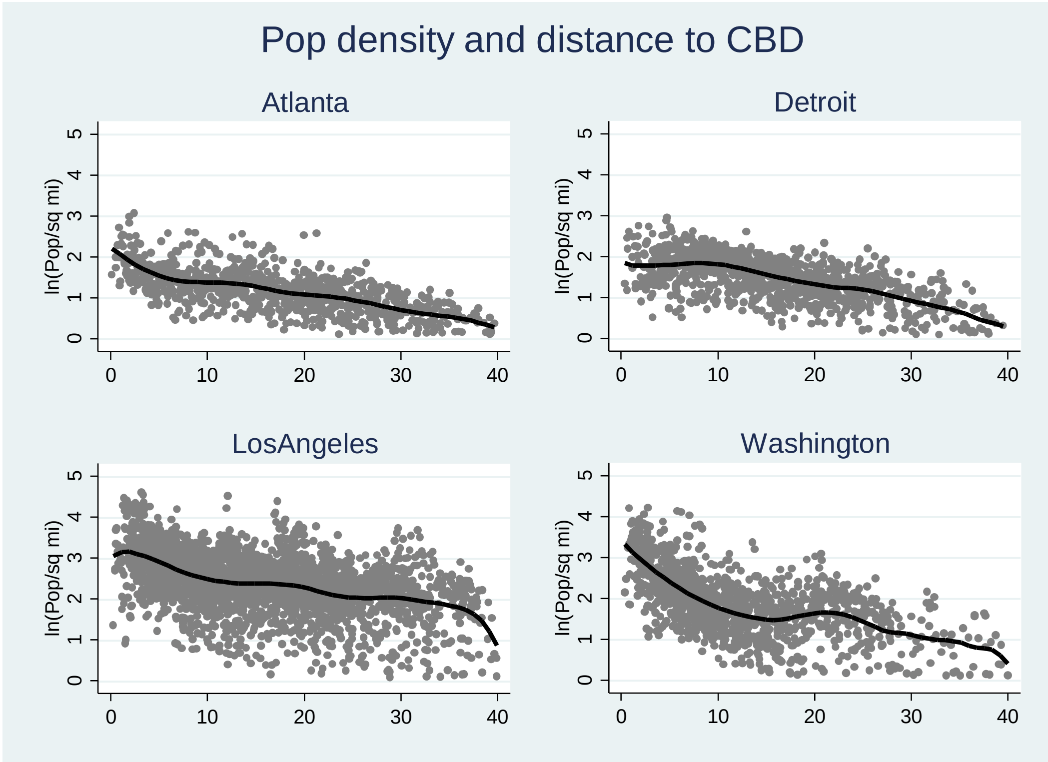


Figure 13: Racial/ethnic concentration by distance to CBD, selected MSAs

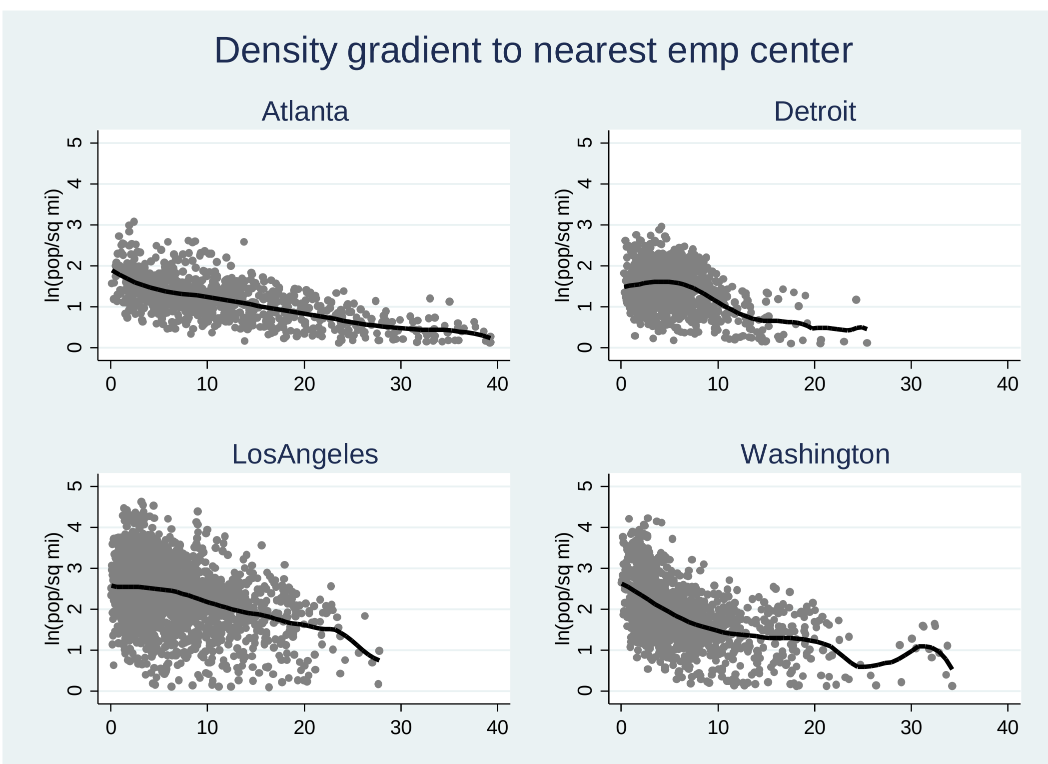


Note: Columns show percent of MSA population by racial/ethnic group.

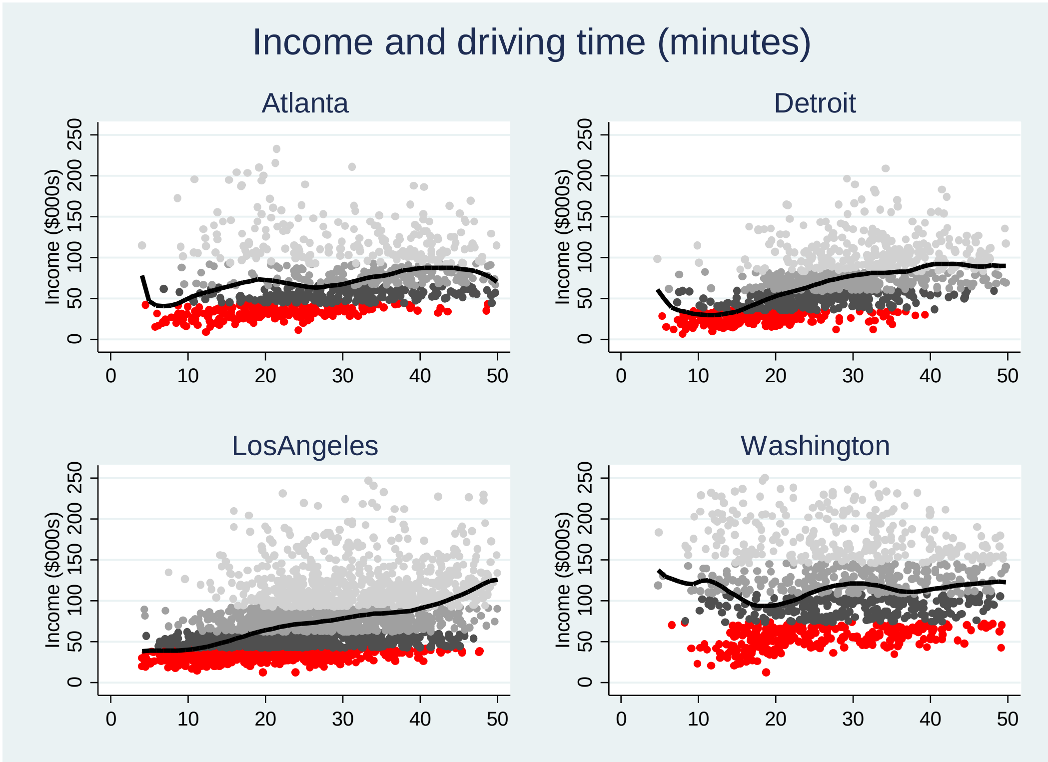
Appendix Figure 1: Neighborhood population density and distance to CBD, selected MSAs



Appendix Figure 2: Neighborhood population density and distance to nearest employment center, selected MSAs



Appendix Figure 3: Neighborhood income and driving time to CBD, selected MSAs



Appendix Figure 4: Neighborhood income and transit time to CBD, selected MSAs