# Exploring Racial and Poverty-based Disparities in Transport Equity Among Large U.S. Metropolitan Areas

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# INTRODUCTION

The goal of contemporary urban transportation planning, simply put, should be to improve transportation accessibility and mobility for a widening arc of society. Improving accessibility means expanding the number and range of proximate travel destinations—including job and educational opportunities, health care opportunities, retail and service opportunities, and social and recreational opportunities. Improving mobility means making it easier and more convenient to travel to those opportunities. Whereas accessibility is about maximizing the number and convenience of potential travel destinations, mobility is about making it easier to make actual trips.[1] In most parts of the U.S. and for most U.S. residents, both of these imperatives have come to center around the private car: improved mobility has come to mean expanded auto availability, while improved accessibility has meant more roads connecting here to there. Still, most is not all, and as America's cities and suburbs become more and more congested, urban transportation planners nationwide are giving welcome attention to non-auto-centric approaches to jointly expanding mobility and accessibility, especially in locations suffering from a dearth of both.

This is important for reasons of both efficiency and equity. Expanded accessibility and mobility are cornerstones of continued economic growth (Litman, 2017; Brown et al., 2009). They are even more essential to social progress (Preston and Rajé, 2007; Lucas, 2004; Church et al., 2000). Indeed, one measure of an unjust society is that it fails to provide adequate access and mobility to those who are physically, economically, or socially disadvantaged. (Lucas, 2012).

Consistent with this view, transportation planning practice is gradually shifting from focusing on growth-oriented system-level measures such as aggregate travel time savings to a view that also incorporates equity: the ability of all members of society to conveniently travel to a full range of economic and social opportunities regardless of their wealth, age, physical condition or demographic characteristics. This shift began more than fifty years ago when Harvard economist John Kain set forth his "spatial mismatch hypothesis." (Kain, 1968). Kain hypothesized that the higher unemployment rates observed among African-American workers (compared to their white counterparts) was partially due to the fact that

Blacks were concentrated in urban neighborhoods while jobs were increasingly moving to the suburbs; and that urban public transportation systems in the U.S. did a poor job connecting cities to suburbs and suburbs to suburbs. A later report by the McCone Commission attributed much of the cause of the 1965 Watts riots in Los Angeles to the paucity of jobs in the Watts neighborhood and to the lack of transportation options connecting Watts to Los Angeles area job centers (Kain, 1992).

Somewhat controversial when it was first proposed, Kain's spatial mismatch (i.e., spatial disparities) formulation has since become the mainstream view; and has been the object of hundreds of individual studies and numerous review papers (see, for example, Holzer, 1991; Preston and McLafferty, 1999; Blumenberg and Manville, 2004; Gobillon et al., 2007). Until the early 1990s, most spatial mismatch studies made use of commute distance as their primary measure of accessibility. More recently, with the availability of detailed census data and local travel surveys, the focus has expanded to consider mobility disparities among different social groups, to use job accessibility, which incorporates both land use and transportation elements, and to emphasize travel time over travel distance when operationalizing mobility and accessibility differences. This has led to a reconsideration and broadening of Kain's original spatial mismatch hypothesis. Recent empirical studies have found that poor and minority residents of inner-urban neighborhoods don't necessarily live further from job opportunities than middle-class and White households, but rather, have less access to private vehicles (Grengs, 2010; Blumenberg and Manville, 2004) and are therefore more dependent on public transit service, particularly bus service. Poorly served by transit service to begin with, many such neighborhoods were further disadvantaged by a succession of transit service cutbacks during the 1970s and 1980s.

More recently, empirical studies of accessibility and mobility disparities have expanded beyond their earlier focus on work trips (which nationally, make up less than 30% of daily trips) to include studying access and ease of travel to supermarkets and retail opportunities (Larson et al., 2009; Aggarwal et al., 2014; Rhone et al., 2017; Caspi et al., 2012), schools and educational opportunities (McDonald, 2012; McDonald, 2008; McDonald et al., 2010; Wilson et al., 2010), parks and recreational opportunities (Weiss et al., 2011; Wolch et al., 2005; Abercrombie et al., 2008; Talen, 1997), and essential health care services (Hare and Barcus, 2007; Wang et al., 2015; Wang and Tang, 2013; Loh et al., 2009). Other studies have focused on the declining availability of affordable housing, noting that poor renters are increasingly being displaced by gentrification from their longtime and familiar communities—in which their transportation options, if not plentiful, were at least well understood—into less familiar and accessible locations(Welch, 2013; Reina et al., 2019). Table 1 summarizes some of the more recent and notable studies of transportation accessibility and mobility disparities.

Still, most recent empirical studies focus *either* on a single activity type (such as jobs *or* shopping *or* health care) *or* take place within a single city or metropolitan area. This makes it difficult to generalize their findings across multiple activities and places and to establish an empirical baseline for a broader set of policy approaches. As a result, researchers don't always agree on policy prescriptions. Some come down on the side of unequal proximity to activity destinations as being the principal problem and conclude that policy should focus on promoting a more spatially homogeneous supply of affordable housing, job, healthcare, retail and recreation opportunities. Others conclude that government policy would do better to focus on expanding mobility options within the existing fabric of neighborhoods and activities by, for example, providing the poor with greater auto mobility. Still other researchers have embraced a combination of the two approaches by advocating a strategy that more heavily weights those transportation projects and services that benefit those populations who have historically been the most transportation disadvantaged (Blumenberg and Manville, 2004; Fan, 2012).

This working paper takes a more comprehensive approach than prior efforts. It considers both accessibility and mobility. It explores accessibility and mobility disparities across neighborhoods comprised of different racial and poverty groups. Last, but not least, it covers all U.S. metropolitan areas with more than 500,000 residents. Being so spatially comprehensive requires imposing some limits on which activities, population subgroups, and accessibility and mobility dimensions are considered. In terms of activity accessibility, we consider five destination types: employment centers, hospitals, day care facilities, public parks, and community libraries. In terms of mobility, we look solely at auto availability. In terms demographics, we compare proximity and mobility measures between all census tracts in a metropolitan area and those in which the 2016 share of African-American and Latino residents was double the metropolitan area average. We also consider those census tracts in which the poverty rate in 2016 was twice the metropolitan-level poverty rate. We do not consider opportunity proximity or mobility disparities across census tracts with higher proportions of other vulnerable groups, such as single-parent households, the disabled, or the elderly.

The balance of this working paper is organized into four parts. Part I introduces the approach, data and measurement systems used to establish our key findings. Part II looks at the proximity disparities to jobs, hospitals, day care, parks, and libraries for residents of census tracts with twice the metropolitan area proportion of African-Americans, Latinos, and households living below the poverty line. Part III focuses on mobility disparities by comparing the proportion of households lacking access to a private vehicle. Part IV identifies what we call "equity worst-case metro areas:" those in which the various proximity and mobility ratings are both much worse than is typical. Part V concludes with a summary of findings and series of federal, state, and local transportation policy and planning equity implications.

| Table 1: Summary of Selected Recent Studies of Job, Hospital, School, and Park Accessibility in U.S. Metropolitan Areas | | | | |
|---|---|---|---|---|
| Activity | Author and Year | Geography & Year | Accessibility & Mobility Measurements | Main Findings |
| Jobs & Employment | Wang (2003) | Cleveland, 1990 | Job *proximity* is measured as the distance between job and housing. Job *accessibility* further considers alternative travel modes, congestion and competition between job opportunities | Low-wage workers have better job proximity, but they have worst job accessibility because of their lower car ownership. |
| | Shen (2000) | 20 largest U.S. metropolitan areas, 1990 | Regression analysis of commute times | While commute times tend to be lower in the city centers, they are higher among low-income census tracts. Regression analysis finds that race, education attainment and car ownership all contribute to low-income resident's longer commute times. |
| | Hu (2015) | Los Angeles, 1990 and 2007-2011 | Comparison of car-based job accessibility between center city and suburban residents. | Inner-city poor residents have better job accessibility than their suburban counterparts. Suburbanization has evened out accessibility differences between the poor and non-poor. The job accessibility of the poor living in the inner city decreased over time. |
| | Grengs (2010) | Detroit, 2000 | Job accessibility is calculated using a gravity model, based on car and public transit travel times. | Car owners have superior job accessibility in almost all census tracts. |
| | Grengs et al. (2010) | San Francisco, 2000 and Washington D.C., 2002 | Job accessibility is calculated using an inter-metropolitan gravity model. | San Francisco has superior overall job accessibility based on its higher highway speeds, but downtown Washington D.C. has better localized accessibility due to superior activity proximity. |
| | Levine et al. (2012) | 38 metropolitan areas in the U.S., 2000-2010 | Job accessibility is calculated using an inter-metropolitan gravity model. | While theory suggests that speed is more important than proximity in determining accessibility, the authors find proximity to be more important in the metro areas analyzed. |
| Hospital Access | Loh et al. (2009) | Jacksonville, Florida, 2005 | Potential vs. actual hospital accessibility | Many residents of economically-deprived communities in central cities have good access to large hospitals. This is not the case for those living in rural and more remote areas. Hospital accessibility is correlated with hospital usage. |
| | Hare and Barcus (2007) | Kentucky, 2003 | Potential and actual distance to the hospital; mean distance to a varying number of the nearby hospitals. | People living in the rural areas travel further to hospitals. Populations living more than 45 minutes from the nearest hospital tend to poorer. |
| | Wang et al. (2015) | US National cancer centers | Minimizes the variance among accessibility to nearby hospitals | Redistributing cancer centers across different geographies could help enhance equitable access to cancer treatments. |
| | Wang and Tang (2013) | Chicago, 2000 | Quadratic programming | To promote greater health care equity, peripheral areas need additional facilities while downtown facilities need additional capacity. |

Table 1 (continued): Summary of Selected Recent Studies of Accessibility & Mobility in U.S. Metropolitan Areas

| Activity | Author and Year | Geography & Year | Accessibility & Mobility Measurements | Main Findings |
|---|---|---|---|---|
| School Access | McDonald (2008) | US, 2001 | Binary logit model of the decision to walk or bike to school | Low-income and minority residents, especially Blacks and Hispanics are more likely to travel to walk or bike to school than are Whites and higher-income residents. |
| | McDonald et al. (2010) | San Francisco, 2006-2007 | Rates of active vs. vehicle travel to school | Neighborhoods with higher levels of community-school involvement are likely to have higher rates of active travel to school. |
| | McDonald (2012) | US, 1977-2009 | Rates of active vs. vehicle travel to school | Male school children are more likely to walk or cycle to school than female students. |
| | Wilson et al. (2010) | St. Paul and Roseville Area, Minnesota, 2009 | Logistic model | School choice programs, which allows students to attend “magnet schools” rather than the closest neighborhood school, result in greater travel distances and lower rates of travel by foot and bicycle. |
| Public Park Access | Talen (1997) | Pueblo, Colorado and Macon, Georgia | Statistical analysis of park access scores | In Macon, residents of neighborhoods with higher home values and higher proportions of White residents have better park access. A similar pattern is evident in Pueblo. |
| | Wolch et al. (2005) | Los Angeles | Spatial mapping of access to parks | Low-income, poverty and neighborhoods with high shares of Latinos, African Americans and Asian-Pacific Islanders have dramatically lower access to park resources and also park funding. |
| | Abercrombie et al. (2008) | Maryland, 2004-2005 | Statistical analysis (ANOVA) of block-level access to private recreational facilities and public parks as a function of median income and the share of the non-white population | Mixed-race neighborhoods have the highest level of public park access. Low-and-middle-income residents of higher-income and white-majority census blocks have the lowest level of public park access. |
| | Weiss et al. (2011) | New York City | Kernel density and distance measurements using GIS | While most African-American and Latino neighborhoods have superior levels of spatial access to public parks, in practice, this advantage is compromised by social disamenities, such as crime, pedestrian safety and noxious land use. |
| Affordable Housing Accessibility | Welch (2013) | Baltimore, Maryland | Connectivity and accessibility of the public transit network | While most of Baltimore's affordable housing units enjoy superior transit access, this is not true for residents of Low-Income Housing Tax Credit projects. |
| | Reina et al. (2019) | US, 2000-2016. Various sources of data | The location affordability index | When analyzed nationally, the Low-Income Housing Tax Credit projects are disproportionately located in minority neighborhoods. |

# I. APPROACH, MEASUREMENT ISSUES, AND DATA SOURCES

### Conceptualizing Accessibility as Distance-based Proximity

Transportation planners generally follow two conventions when conceptualizing accessibility. The first is that more destination choices are better than fewer choices, and the second is that closer or more proximate destinations are preferable to more distant ones.[1] Proximity between origin(s) and destination(s) is typically measured as travel distance and/or travel time along a street or transit network.

These days, any empirical examination of accessibility should probably start with the auto, transit, and pedestrian accessibility estimates produced by the University of Minnesota's Accessibility Observatory (http://www.access.umn.edu/ ). These estimates, which cover job accessibility only, are produced annually for the nation's 50 largest metropolitan areas. In terms of auto accessibility, the Accessibility Observatory uses a detailed roadway network to measure the population and proximity-weighted travel time between every census block and every major job center. Travel speeds are calculated using data that reflect typical conditions for an 8 a.m. Wednesday morning commute trip.

In terms of transit accessibility, the Accessibility Observatory team makes use of rail and bus schedules as made available via the federally-supported General Transit Feed Specification (GTFS) format first developed by Google and Portland TriMet. In terms of pedestrian accessibility, the Accessibility Observatory considers jobs within a 60-minute travel time sidewalks and other pedestrian-oriented rights-of-way.

Although not as sophisticated as the Accessibility Observatory's, our measurements include more destination activities than just jobs. Instead of estimating travel time, we measure proximity as defined by straight-line distance. This is sometimes referred to as aerial or Euclidean distance, whereas network distance is known as "Manhattan distance."

In terms of identifying trip origins, we make use of census tracts—in contrast to the Accessibility Observatory, which uses the more detailed census block geography. Census tract-level data from the American Community Survey (ACS), which includes detailed demographic, income, housing, and journey-to-work characteristics, first became available in 2015.[2] Complete, census tract-level ACS data is currently available at the census tract level for all U.S. metropolitan areas with a 2016 population of 500,000 or more.

Like the Accessibility Observatory, we observe the convention that accessibility increases with the number of destination opportunities within a specified time or distance threshold. Nevertheless depending on the destination activity, we do not necessarily discount more distant destinations over closer ones.[3] Because all of our ensuing accessibility measurements are based on aerial distances rather than travel times, and because we don't automatically discount more distant activities, we will henceforth refer to our measurements as linear distance-based proximity measures rather than as accessibility measures.

All told, we consider five sets of distance-based proximity measures:

- <u>Job Center Proximity:</u> Most households have at least one member who commutes to work daily. According to the Census Bureau, nationally, the average one-way commute trip currently takes 26.1 minutes.

Among the 107 metropolitan areas in this study, Wichita (Kansas) has the shortest average commute time at 19.4 minutes, while the New York-Newark metro area has the longest at 35.9 minutes. When choosing a job, most workers put considerations of salary, benefits and skills-match ahead of commuting time. This means that they will generally be willing to travel greater distances for additional and/or better-paying job opportunities, and not necessarily choose the closest available job. Accordingly, when measuring job proximity, we measured the linear distance between each census tract centroid and the point locations of *all* metropolitan area primary job centers with more than 10,000 workers. Job counts were calculated using annual employment counts from the Census Bureau's County Business Patterns series, which tabulates jobs by zip code and is downloadable from https://www.census.gov/data/datasets/2016/econ/cbp/2016-cbp.html .

As expected, the number of primary job centers tends to vary with metropolitan area size and population. Measured in absolute terms the New York City-Newark metropolitan area has the most primary job centers at 227, while Syracuse has the fewest with just one. The picture changes slightly when primary job centers are measured on a per capita or per worker basis. At 1.92 job centers per 100,000 residents, Harrisburg (Pennsylvania) is the metro area with the most primary job centers, while Syracuse (with 0.15 job centers per 100,000 residents) is the metro area with the fewest.

As Table 2 (which lists the ten metro areas with the largest and smallest distance-based proximity measures for each activity type) reveals, when measured in this manner, job proximity is found to vary from a low of 10.8 kilometers in the Cape Coral (Florida) metropolitan area, to a high of 7.7 kilometers for the Modesto metropolitan area, California. Note that when comparing proximity measures across metro areas, we refer to shorter average distances to large job centers as indicative of better proximity, and longer distances as indicating worse proximity. The average travel distance to regional job centers among all 107 metropolitan areas is 9.9 kilometers.

Proximity to more jobs does not necessarily equate to proximity to better jobs, and this analysis makes no effort to look at the quality of the skills match between commuters and potential jobs. It may be, for example, the better quality of jobs or the higher salaries paid make it more than worthwhile for many workers to prefer jobs that are less accessible in terms of distance over jobs that are more accessible.

- Hospital Proximity. Most people don't need everyday access to a hospital, but for those requiring treatment for chronic diseases or emergency medical care, being closer to a hospital is better than being farther away. Likewise, because many households' insurance plans stipulate that they use particular hospitals or doctors (and not necessarily the closest one) having access to more hospitals and health care facilities is preferable to having access to just one or two.[4] For this study, we calculated the average Euclidean distance to all hospitals within ten miles of the centroid of every census tract in each metropolitan area. As input into this process, a GIS shapefile including the locations of 7,570 currently-operating hospitals in the U.S. was downloaded from a website maintained by the U.S. Department of Homeland Security

Table 2: Top 10 and Bottom 10 U.S Metropolitan Areas Sorted by Distance-based Proximity (LDBP) Measures

| Destination Activity ▶ | Average Distance (km) to Large Job Centers by Metro | | Average Distance (km) to Hospitals by Metro | | Average Distance to 5 Closest Day Care Centers | | Average Distance to Closest Public Park by Metro | | Average Distance to Closest Library by Metro | |
|---|---|---|---|---|---|---|---|---|---|---|
| All 107 Metropolitan Areas | Mean Distance (km) | 9.9 | Mean Distance (km) | 9.2 | Mean Distance (km) | 3.7 | Mean Distance (km) | 3.9 | Mean Distance (km) | 3.9 |
| | Median Dist. (km) | 10.0 | Median Dist. (km) | 9.3 | Median Dist. (km) | 3.6 | Median Dist. (km) | 3.1 | Median Dist. (km) | 4.0 |
| | Std. Dev. | 0.5 | Std. Dev. | 0.8 | Std. Dev. | 1.4 | Std. Dev. | 2.6 | Std. Dev. | 0.9 |
| Top 10 Metropolitan Areas (sorted low-to-high by average distance) | Modesto CA | 7.7 | Stockton CA | 7.2 | San Jose CA | 1.4 | San Jose CA | 1.1 | New York NY | 1.7 |
| | Stockton CA | 7.9 | Modesto CA | 7.3 | Los Angeles CA | 1.5 | San Francisco CA | 1.2 | Los Angeles CA | 2.1 |
| | Bakersfield CA | 8.6 | Lexington KY | 7.4 | New York NY | 1.5 | Los Angeles CA | 1.3 | San Francisco CA | 2.2 |
| | Scranton–WB PA | 9.0 | New Haven CT | 7.4 | San Francisco CA | 1.5 | Chicago IL | 1.3 | Boston MA | 2.3 |
| | Worcester MA | 9.0 | Worcester MA | 7.5 | Bridgeport CT | 1.6 | Honolulu HI | 1.3 | San Jose CA | 2.3 |
| | San Francisco CA | 9.1 | Durham NC | 7.7 | Miami FL | 1.7 | Modesto CA | 1.4 | Honolulu HI | 2.5 |
| | Portland ME | 9.1 | Syracuse NY | 7.8 | New Haven CT | 1.7 | San Diego CA | 1.5 | Chicago IL | 2.5 |
| | McAllen TX | 9.1 | Providence RI | 7.8 | San Diego CA | 1.8 | Milwaukee WI | 1.5 | Springfield MA | 2.5 |
| | Harrisburg PA | 9.1 | Bridgeport CT | 7.9 | Stockton CA | 1.8 | Bridgeport CT | 1.8 | Miami FL | 2.5 |
| | Lexington KY | 9.2 | Boise City ID | 8.0 | Hartford CT | 2.0 | Stockton CA | 1.8 | New Orleans LA | 2.6 |
| Bottom 10 Metropolitan Areas (sorted high-to-low by average distance) | Cape Carol FL | 10.8 | Los Angeles CA | 10.2 | Boise City ID | 10.4 | Lancaster PA | 15.0 | Chattanooga TN | 6.5 |
| | Fayetteville AR | 10.8 | Phoenix AZ | 10.2 | Provo UT | 7.5 | Birmingham AL | 12.4 | Fayetteville AR | 6.2 |
| | Las Vegas NV | 10.7 | Columbia SC | 10.1 | New Orleans LA | 6.9 | Columbia SC | 11.9 | Cape Carol FL | 5.7 |
| | Atlanta GA | 10.6 | Dallas TX | 10.1 | Chattanooga TN | 6.2 | Augusta GA | 10.6 | Augusta GA | 5.6 |
| | Durham NC | 10.6 | Atlanta GA | 10.1 | Grand Rapids MI | 6.2 | Portland ME | 10.4 | Nashville TN | 5.3 |
| | Denver CO | 10.5 | Richmond VA | 10.1 | Worcester MA | 6.1 | Little Rock AR | 9.6 | Lakeland FL | 5.3 |
| | Detroit MI | 10.5 | Chicago IL | 10.1 | Portland ME | 6.0 | Fayetteville AR | 9.0 | Columbia SC | 5.2 |
| | Riverside CA | 10.5 | Denver CO | 10.1 | Nashville TN | 5.9 | Lakeland FL | 8.8 | Greenville SC | 5.2 |
| | Minneapolis MN | 10.5 | New York NY | 10.1 | Birmingham AL | 5.6 | El Paso TX | 8.4 | Greensboro NC | 5.2 |
| | Raleigh NC | 10.5 | Detroit MI | 10.1 | Fayetteville AR | 5.6 | Youngstown OH | 7.8 | Little Rock AR | 5.1 |

(https://hifld-geoplatform.opendata.arcgis.com/datasets/a2817bf9632a43f5ad1c6b0c153b0fab_0/data). Once downloaded and geocoded, this list was pruned of all facilities that do not operate general and acute care facilities open to the public.

As Table 2 indicates, the spatial distribution and geographic density of hospitals varies widely by metropolitan area, resulting in significant differences is hospital proximity. The five metro areas with the highest level of hospital proximity when measured in terms of distance include Stockton and Modesto in California; Lexington (Kentucky), Worcester (Massachusetts), and New Haven (Connecticut). The five metro areas with the lowest average proximity scores include Los Angeles, Phoenix, Dallas-Ft. Worth, Atlanta, and Columbus in South Carolina. Among the 107 metro areas in our study, the average distance to all hospitals within a 10-mile radius is 9.2 kilometers.

For hospitals as for jobs, quality will tend to matter more than quantity. Except those needing immediate trauma care, most seriously-ill patients would willingly travel greater distances to be admitted to a better-quality hospital than shorter distances to be gain admission to a less well-regarded hospital. Moreover, because hospital admission privileges may be linked to health insurance providers, having physical access to a nearby hospital does not necessarily mean that a patient can be admitted. These latter issues—neither of which are incorporated into our measurements—serve to reduce the value of physical proximity when comparing and evaluating health care opportunities across metropolitan areas.

- Day Care Proximity. Easy access to day care facilities is important for parents seeking to balance work and family commitments, especially for single-parent households and households with two working parents unable to afford in-home childcare. A recent study by the Center for American Progress (Center for American Progress, 2016) reports that the last several decades have seen a dramatic increase in the maternal labor participation rate of dual-earner families, further expanding the demand for day care. On the supply side, day care licensing and regulation is almost entirely a state matter and some states make it easier to establish and run day care facilities than others (Extension, 2015).

  To what extent does access to day care vary systematically by metropolitan area? To find out, we downloaded a current geodatabase of all registered day care facilities in the U.S. as maintained by the U.S. Department of Homeland Security (https://hifld-geoplatform.opendata.arcgis.com/datasets/650ac2c0808c482bbd29c101a189f3dc_0 ). After eliminating those facilities attached to religious membership organizations and/or employers, this left us with 83,425 separate day care centers. Note that this database does not include any information on the age-orientation or number of available day care slots, on the level of supervision, or any licensing provisions. For each census tract centroid, we then calculated the average aerial distance (by metropolitan area) to the closest five-day care facilities. As Table 2 shows, the average day care facility proximity measure varies widely from a least-accessible high of 10.4 kilometers for Boise (Idaho) to a most-accessible low of 1.4 kilometers for San Jose in California. Among the 107 metro areas in our sample, the average distance to the nearest three day care centers is 3.7 kilometers.

As with jobs and hospitals, proximity is only part of the story. On the one hand, many if not most parents would happily given up proximity to more day care facilities in favor of better facilities. On the other hand, to the extent that parents of all incomes have convenient access to more day care options and facilities, competition between providers will hopefully promote both greater quality and reduced prices.

Among the 107 metro areas considered in this study, the number of day care centers per 100,000 residents ranges from a high of 75.9 in the Bridgeport (Connecticut) metropolitan area to a low of 4.5 in Provo (Utah).

- Public Park Proximity**.** By virtue of their greater wealth, higher-income households generally have greater access to recreational opportunities than poorer ones (Cohen et al., 2013; Hillier, 2008). For many poor households, their only free recreational opportunity is the nearest public park. Public parks also serve as important mixing spaces for all segments of society. And for many city-dwellers, nearby public parks serve as their principal opportunity for interacting with nature on a daily or weekly basis. Park professionals have long published per capita guidelines for park size and access (National Recreation and Park Association, 2016) but in practice, the degree to which municipalities meet those guidelines varies widely by location and according to when the municipality was developed. For the purpose of comparing park proximity across metropolitan areas, we first obtained a GIS shapefile of all federal, state, county, and local public parks and park facilities in the United States. Available from the ESRI ArcGIS website at https://www.arcgis.com/home/item.html?id=578968f975774d3fab79fe56c8c90941 this file includes information on the locations, types, and acreage of all park facilities larger than 0.1 acres. Because many of the facilities on this list included plazas and non-park public spaces, we limited our subsequent proximity analysis to those sites greater than 0.01 square miles (or 6.4 acres). We then measured the distance from each census tract centroid to the nearest public park. Unlike the previous cases where we calculated the average distance to multiple job centers, hospitals and day centers, in this case, we assumed that residents would prefer to visit the nearest park to their home rather than have a choice of parks of varying distances.[5]

  Of the five activity destinations considered in this study, park proximity is the one that varies the most widely. As Table 2 reveals, residents of San Jose, California need travel an average of just 1.1 kilometers to visit their nearest park. At the other extreme, residents of the Lancaster (Pennsylvania) metro area must travel an average of nearly 15 kilometers to get to the nearest public park. For the sample as whole, the average distance to the nearest public park is 3.88 kilometers. In terms of park supply, at 4.7 square miles per 100,000 residents, Tucson, Arizona offers its citizens the most park land, while Salt Lake City, at just under 0.01 square miles per 100,000 residents offers its citizens the least.

- Library Accessibility**.** Many Americans younger than 25 have probably never been to a public library; they get their reading material by downloading it or having it delivered to their doorstep. By contrast, for most Americans over the age of 50, the local public library occupies a central role in their memory as the place they were able to explore a wide range of literary worlds for the price of just a library card. Beyond simply being a place to borrow books (or later tapes and CDs), libraries function as the cultural and social centers of their communities for a diverse set of age and demographic groups.

Distance to libraries varies widely by region and place. Municipalities in the Northeast and Midwest, which saw their major growth spurts occur before 1950, tend to have more public library branches and more sole-purpose library buildings. Cities in the South and West, by contrast, which mostly developed around the private automobile have a greater tendency to co-locate their libraries with schools and other municipal buildings. For the purposes of this study, we made use of the LibWeb's (https://www.lib-web.org/united-states/ ) online list of the locations of all the public libraries in the United States. After pruning the list of mobile libraries and school-only libraries (which may be open to the public but have limited hours), we identified 16,605 separate library facilities throughout the country. We then calculated the Euclidean distance between each census tract centroid in our sample of 107 metropolitan areas and the closest nearby public library.

As with parks, distances to the nearest library vary widely across metropolitan areas (Table 2). Residents of the New York City-Newark metropolitan area, for example, need travel an average of just 1.7 kilometers to get to their nearest library. At the opposite extreme, Chattanooga residents must travel an average distance of 6.5 kilometers to get to their nearest library. Averaged over all 107 metro areas, residents must travel an average of 3.9 kilometers to the nearest library.

### How Proximity Varies (or Doesn't Vary) with Metro Area Size, Location, Income, and Spatial Structure

Appendix B includes a full listing of average distance measures for the five activity types (jobs, hospitals, day care facilities, parks, and libraries) for all 107 metropolitan areas included in this study. As a precursor to profiling proximity disparities by race and income, we first consider the degree to which these measures systematically vary by metropolitan area size, location, and spatial structure. To do so, Table 3 presents a listing of correlation coefficients comparing the five activity-based proximity measures (in columns) to each other, to the number of facilities per 100,000 residents, to measures of population size and changes, to measures of income and poverty, by region, and by seven measures of metropolitan spatial structure.

- <u>Cross-activity Proximity Correlations</u>: Since the five activity types offer different services and experiences, there is little reason to believe that their respective proximity measures should be correlated with one another. As Table 3 shows, with a few exceptions, this is indeed the case. The two principal exceptions are proximity to job centers and hospitals; and, to a much lesser extent, day care and park proximity. In metro areas where commuters travel farther to work, they also travel farther for health care. Likewise, in metro areas where residents travel farther for their day care choices, they also travel farther to the nearest park.

Table 3: Correlation Coefficients Comparing Distance-based Proximity (DBProx) Measures by Region, and to Facility Levels, Population and Income Measures, and Metropolitan Spatial Structure

| Metro Area Characteristic | | Average (Km) Proximity to Large Job Centers | Average (Km) Proximity to Hospitals | Average (Km) Proximity to Nearest 5 Day Care Facilities | Average (Km) Proximity to Nearest Park | Average (Km) Proximity to Nearest Library |
|---|---|---|---|---|---|---|
| Distance-based Proximity (Km) Measures | Average DBProx to Large Job Centers | 1.00 | | | | |
| | Average DBProx to Hospitals | 0.86* | 1.00 | | | |
| | Average DBProx to Nearest 5 Day Care Facilities | 0.08 | -0.02 | 1.00 | | |
| | Average DBProx to Nearest Park | 0.00 | -0.04 | 0.36* | 1.00 | |
| | Average DBProx to Nearest Library | 0.07 | 0.08 | -0.12 | 0.09 | 1.00 |
| Centers and Facilities per 100,000 residents | Large Job Centers per 100,000 residents | 0.33* | | | | |
| | Hospitals per 100,000 residents | | -0.02 | | | |
| | Hospitals beds per 100,000 residents | | 0.05 | | | |
| | Day Care Centers per 100,000 residents | | | -0.51* | | |
| | Parks per 100,000 residents | | | | -0.45* | |
| | Park Area (square miles) per 100,000 residents | | | | -0.38* | |
| | Libraries per 100,000 residents | | | | | -0.04 |
| Population Measures | Metro Area Population, 2017 | 0.33* | 0.42* | -0.40* | -0.31* | 0.02 |
| | Metro population > 2 million (0/1) | 0.43* | 0.49* | -0.38* | -0.37* | -0.03 |
| | Metro population: 1 - 2 million (0/1) | 0.07 | 0.12 | 0.11 | -0.02 | -0.04 |
| | Metro population: 0.5 - 1 million (0/1) | -0.46* | -0.55* | 0.27* | 0.36* | 0.06 |
| | Percent Population Change, 2000-2017 | 0.00 | -0.12 | 0.26* | 0.19 | 0.34* |
| Income Measures | Median Household Income, 2017 | 0.08 | 0.06 | -0.35* | -0.38* | -0.07 |
| | Poverty Rate, 2017 | -0.19 | -0.05 | 0.04 | 0.16 | 0.07 |
| | 95-20% Income Ratio | | | | | |
| Regional Fixed Effect Measures | Northeast Region (0/1) | -0.21 | -0.33* | -0.10 | 0.05 | 0.01 |
| | Midwest Region (0/1) | 0.06 | 0.07 | 0.25* | -0.15 | -0.02 |
| | Southeast Region (0/1) | 0.24* | 0.19 | 0.09 | 0.34* | 0.08 |
| | Western Region (0/1) | -0.13 | 0.03 | -0.22 | -0.31* | -0.09 |
| Spatial Structure Measures | NLCD-based Population Density 2010 | -0.03 | 0.09 | -0.49* | -0.41* | 0.03 |
| | Core Area Population Share, 2010 | -0.35* | -0.38* | 0.00 | -0.35* | 0.20 |
| | Core Area Population Growth Rate, 2000-2010 | -0.11 | -0.24 | -0.14 | 0.11 | -0.05 |
| | Density Gradient Intercept Value, 2010 | 0.16 | 0.39* | -0.43* | -0.51* | 0.01 |
| | Density Gradient Slope Coefficient Value, 2010 | -0.03 | 0.00 | 0.24* | 0.17 | 0.15 |
| | Employment Moran's I, 2013 | -0.14 | -0.31* | 0.15 | 0.33* | -0.02 |



* indicates statistical significance at the .01 level

- Proximity and Opportunity: All else being equal, we should expect proximity to be correlated with opportunity. In metro areas where jobs and urban services are more plentiful (when measured on a per capita basis), we might also expect those services to be less distant. Yet as the second set of rows in Table 3 (marked "Centers and Facilities per 100,000 residents") indicates, this relationship between frequency and distance doesn't always hold. In the case of job centers, there is a positive and statistically significant correlation between the number of large job centers in a metro area and the average distance commuters must travel to them. In the case of hospitals, there is no relationship between the number of hospitals or hospital beds per 100,000 residents) in a metro area and the average distance to those hospitals. Likewise, in metro areas with more libraries (per 100,000 residents), those libraries aren't systematically nearer to residents.

  The two facility types for which frequency and proximity do seem to be correlated are day care and parks. In metro areas where day care facilities are more plentiful, they are also, on average, closer to residents. Because most day care facilities are privately-run and must compete for business, and because being closer to potential clients is one way to compete, this isn't particularly surprising. What is surprising is the fact that park availability and proximity are similarly related: in metro areas with more parks (per 100,000 residents), those parks are arranged in such a way as to be more accessible. This suggests that the municipal authorities in charge of locating park facilities are doing so in a manner that accounts for resident access.

- Population Size and Proximity: This could go either way. On the one hand, to the extent that urban activities like day care centers compete on location, with each provider attempting to carve out their own market or catchment area, we should not expect to observe a relationship between metro area size and activity proximity. On the other hand, to the extent facilities like schools, parks, or libraries exhibit economies of scale—meaning that fewer big facilities can more efficiently serve the local citizenry than can additional smaller facilities—we would expect proximity to be inversely correlated with metro area size. As the third group of rows in Table 3 (marked "Population Measures") indicates, for jobs and hospitals, the scale economies effect dominates the competition effect, with the result that residents of larger metro areas travel farther on average to large job centers and hospitals than residents of smaller metro areas. The opposite is true for day care and parks, which are more accessible to residents of larger metro areas than smaller ones. Proximity to libraries does not vary with metro area size. In terms of population growth and accessibility, residents of faster-growing metro areas must generally travel greater distances to get to day care centers and libraries than residents of slower-growing ones. Note that none of these relationships accounts for the potential effects of congestion.

- Income Effects: Economic theory suggests that the value that people put on proximity should increase with income and wealth. As people earn more income or accrue greater wealth, they are typically willing to pay more for convenience and access (Crane and Crepeau, 1998). This is so for all types of opportunities and activities. Thus, we would expect residents of wealthier and higher-income metropolitan areas to demand more and greater proximity than residents of poorer ones.

As the results reported in the "Income Measures" columns of Table 3 reveal, this isn't the case in practice. When compared at the metropolitan scale, the only statistically-significant associations between income level and proximity are for day care and parks. As expected, this association is negative, indicating that day care centers and parks are located closer to residents of higher-income metropolitan areas than to residents of lower-income metros. Average proximity to jobs, hospitals, and libraries does not vary systematically with income. Nor is it the case that higher levels of poverty are associated with reduced proximity, at least when measured at the metropolitan scale.

- Proximity and Regional Location: Regional location is more of a proxy for other characteristics (such as housing stock age, density, neighborhood type, and the presence or lack of transportation services) than it is something of intrinsic interest. So, with a few exceptions, it is not surprising that regional location is not highly correlated with any of the five distance-based proximity measures. The major exceptions are for parks—compared to residents of Northeastern and Midwestern metropolitan areas, residents of metro areas in the South travel longer greater distances to parks, while residents of metro areas in the West travel shorter distances. Residents of Midwestern metro areas generally travel longer distances to day care opportunities than residents of metro areas in other regions, while residents of Northeastern metropolitan areas are closer to hospitals.

- Proximity and Metropolitan Spatial Structure: How much does spatial structure affect metropolitan accessibility? By spatial structure, we mean the geographic pattern of residential densities and employment locations. Most U.S. metropolitan areas are characterized by a downward-sloping density gradient, meaning that residential densities are typically highest near the city center and then decline with distance. The shape of this density gradient can be expressed in two numbers: (i) the intercept value, which indicates the density at the city center (where the density gradient intercepts the y-axis); and, (ii) the slope coefficient, which indicates the rate of density decline. Density gradients for older U.S. metropolitan areas generally have higher intercept values (indicating that their central neighborhoods are more densely developed) and are also more steeply-sloped. By contrast, the density gradients for newer metropolitan areas are characterized by smaller intercept values and less negative slope coefficients.

  The final set of rows correlation coefficients presented in Table 3 compare these metropolitan density gradient values with our five activity-based distance measures. To the degree that denser and more compact metropolitan areas offer greater proximity, we would expect to observe a positive correlation between proximity and the intercept value, and a negative correlation between proximity and the slope coefficient. Table 3 also compares proximity with three other measures of metropolitan spatial structure: average residential density, core area population share and growth rate, and the degree of employment clustering. [6]

  As Table 3 reveals, these associations vary widely by both activity type and spatial structure measure. In terms of population density, residents of higher-density metropolitan areas have greater-than average proximity to day care facilities and parks, but not job centers, hospitals, or libraries. Residents of metropolitan areas with more populous urban (i.e., core area) neighborhoods generally have greater job, health care and park proximity than residents of metropolitan areas in which the population is distributed among suburban neighborhoods. Residents of metropolitan areas with dense urban centers (i.e., those with higher density gradient intercept values) have worse hospital proximity but better day care and park proximity. Density gradient slope coefficient values are generally un-correlated with proximity. Lastly, judging from the lack of statistical significance of its correlation coefficient, proximity to job centers is neither better nor worse in metro areas where those job centers are spatially clustered (as indicated by higher values of Moran's I). By contrast, health care proximity is better and park accessibility is worse in metropolitan areas with more clustered job centers.

The correlation coefficients reported in Table 3 are interesting but hardly conclusive. For one thing, they represent associations measured at the metropolitan scale and not the preferences of individual households. For another, except for the journey-to-work and good-quality schools, there is not a lot of evidence suggesting that households choose their residential locations based on maximizing or satisficing their proximity to urban facilities such as hospitals, parks, day care facilities, or libraries. Lastly, many residents are happily willing to trade-off improved proximity for other qualities, for example, health care quality in the case of hospitals, cost and quality in the case of day care, and facility variety and quality in the case of parks. So, while we should not expect proximity to vary systematically as a function of particular metropolitan area socio-economic or locational characteristics, we should insist that no metropolitan area resident suffer from systematic proximity disparities based on their race, ethnicity or income.

## The 2X Disparity Approach

Instead of measuring transportation and travel disparities by population or household type as is commonly done, we measure them by location. In particular, we compare our various proximity estimates between all census tracts in a given metropolitan area to comparable proximity estimates for census tracts in which the proportions of Black, Latino, or poor residents *are double the average* for that same metropolitan area. We will henceforth refer to this latter set of census tracts as "2x tracts"

As Appendix A (which lists the metro-level proportion of African-Americans, Latinos, and those living in poverty for every metro area included in this study) reveals, the 2X proportion and the share of 2X tracts vary widely by metropolitan area. For African-Americans, the 2X proportion varies from a low of one percent in the Provo-Orem (Utah) and McAllen (Texas) metro areas to a high of 98 percent for the Jackson (Mississippi) metro area. For Latinos, the 2X proportion varies from a low of three percent in the Pittsburgh metro area to a high of 180 percent[7] in the McAllen metro area. In terms of the share of population living in poverty, the 2X proportion varies from a low of 17 percent in Washington, D.C. to a high of 64 percent in McAllen (Texas).

The 2X approach allows us to compare proximity between all census tracts in a metropolitan area and those tracts in which minorities and the poor are spatially concentrated. It does not, however, compare the proximity characteristics of different types of residents *within a 2X tract*. This means that a White or Latino household living in a tract designated as "2x" in terms of its proportion of African-American households will be assigned the same proximity values as Black households living in the same tract.

### Measuring Mobility as Carlessness

Opportunity-based travel distance is only one part of the travel behavior story. Another part concerns mobility, the physical ability to actually make a trip. Mobility varies by mode as well as location and destination activity. Among urban residents, those with ready access to private vehicles generally have greater mobility to most activities and locations than those who are dependent on public transportation. This is especially true in in the U.S., where car-dependent suburban development forms predominate. Mobility also varies with income and wealth, and they in turn are correlated with race, ethnicity, and household type (Blumenberg and Manville, 2004).

Because of data limitations, this study takes a more limited approach to measuring mobility. In particular, we measure a lack of mobility as *carlessness*—as the share of households in each census tract lacking access to a privately-owned vehicle. Both the Decennial Census and the ACS count households according to the number of private vehicles they own or have access to. Both also count the number of trips by different modes, but this tabulation is limited to work trips. As with our proximity-based measurements of accessibility, we estimate mobility by location rather than demographic or socio-economic group. This is to say that we compare rates of carlessness between all census tracts in a metropolitan area and those specific census tracts designated as "2X" in terms of their proportions of African-American, Latino, and poor residents.

This approach has a number of limitations. For one thing, it treats all households in 2X census tracts as similar regardless of their individual socio-economic characteristics. For another, it doesn't distinguish between different levels of auto availability. A household that owns three cars has greater auto-mobility than a household that owns one or two cars, but without knowing its particular demographic make-up, we can't easily say how much more. Third, with the recent rise of affordable ride-hailing services like Uber and Lyft, not owning a car doesn't necessarily mean that a household lacks auto-mobility. Indeed, a number of recent studies have demonstrated that the mobility-enhancing effects of Uber and Lyft service are much greater for poor households and those lacking cars than for the population as a whole (Brown, 2018; Brown, 2017). Lastly, and potentially most important, we do not consider the frequency, price, and convenience of local public transit service as an alternative to owning a car. There are a handful of U.S. metropolitan areas where, depending on one's lifestyle, home location and destination choice set, public transit service is both frequent and convenient enough to substitute for owning a car. There are many other U.S. metropolitan areas—the great majority in fact—where public transit service is so limited that even the poorest of households must have ready access to a car.

## II. DISTANCE-BASED PROXIMITY DISPARITIES

Having introduced our basic approach, we now present our major findings. This section identifies metro areas in which there are significant proximity differentials between minority or economically-disadvantaged neighborhoods—the census tracts we have identified as "2X tracts"—and the larger metropolitan area. As noted previously, 2X census tracts are those in which the proportions of African-American, Latino, and poor residents are double (or more) the comparable metropolitan minority or poverty percentage. These comparisons are reported in percentage form: as the difference between the average "as-the-crow-flies" distance to job centers, hospitals, day care centers, parks, and libraries for all census tracts in a metropolitan area; and the comparable distances for 2X Black, Latino, and Poverty census tracts. Because distance is the inverse of proximity (i.e., more distant places have less proximity), places and activities which have negative distance differentials are actually more accessible. Conversely, a report of a positive differential indicates that a place or activity suffers from reduced proximity. Differentials of ten percent or less should be regarded as too small to be noteworthy. These 2X differentials are listed for all 107 metro areas in Appendix C.

In addition to identifying a "Top 10" and "Bottom 10" set of metro areas for each combination of 2X tracts and activity types, we also list the proximity differentials for the nation's ten largest metro areas.

- Job Proximity Disparities: Table 4A identifies the twenty metro areas in which the residents of 2X Black, Latino, and Poverty tracts have significantly better and/or worse proximity to regional job centers. It also lists job proximity differentials for 2X Black, Latino, and Poverty tracts in the nation's ten most populous metro areas. Among all 2X African-American tracts (those in which the proportion of African-American residents is twice the metropolitan total) the average job proximity differential across all 107 metro areas is a modest -2.5%. This means that residents of those tracts are 2.5 percent *closer* to nearby job centers than do commuters elsewhere in the same metropolitan area. Residents of 2X Latino census tracts have a 1.6% proximity advantage to local job centers, while commuters who live in 2X Poverty tracts have a 6.3% proximity advantage. Note that these percentages all refer to differences in proximity, not actual commuting distances. Based on where particular jobs are located, the match between worker skills and employer needs, and the local incidence of traffic congestion, it is quite possible—and in metro areas where job centers are distinguished from one another by industry and employer type, actually quite likely—that what we identify as a numerical proximity advantage may not translate into a shorter or less time-consuming commute trip in the real world.

These results are unexpected. Instead of being less accessible to jobs—the case put forward in 1968 by John Kain in his spatial mismatch hypothesis—workers who live in 2X African-American census tracts actually enjoy greater job proximity.

Table 4A: Top 10 and Bottom 10 U.S. Metropolitan Areas based on Race and Poverty-based JOB CENTER Proximity Differentials

| | Proximity Differentials for 2X African-American Tracts | | Proximity Differentials for 2X Latino Tracts | | Proximity Differentials for 2X Poverty Tracts | |
|---|---|---|---|---|---|---|
| All 107 Metropolitan Areas | Average Differential | -3% | Average Differential | -2% | Average Differential | -6% |
| | Median Differential | -2% | Median Differential | -1% | Median Differential | -5% |
| | Differential Std. Dev. | 7% | Differential Std. Dev. | 12% | Differential Std. Dev. | 9% |
| Top 10 Metropolitan Areas in order of JOB CENTER Proximity Advantage | Deltona FL | -37% | Bakersfield CA | -43% | Daytona Beach FL | -42% |
| | Lancaster PA | -24% | Boise ID | -37% | Austin TX | -35% |
| | Bakersfield CA | -21% | Lancaster PA | -31% | Boise ID | -26% |
| | Worcester MA | -18% | Portland ME | -21% | Spokane WA | -25% |
| | Porland ME | -17% | Spokane WA | -20% | Worcester MA | -23% |
| | Syracuse NY | -16% | Worcester MA | -17% | Lancaster PA | -23% |
| | Chattanooga TN | -15% | Scranton-WB PA | -13% | Portland ME | -23% |
| | Sarasota FL | -14% | Milwaukee WI | -12% | Chattanooga TN | -21% |
| | Modesto CA | -12% | Syracuse NY | -12% | Honolulu HI | -19% |
| | Santa Rosa CA | -12% | Madison WI | -12% | Bakersfield CA | -19% |
| Bottom 10 Metropolitan Areas in order of JOB CENTER Proximity Disadvantage | Houston TX | 5% | Columbia SC | 6% | Houston TX | 2% |
| | San Diego CA | 5% | Little Rock AR | 6% | Louisville KY | 2% |
| | Dayton OH | 5% | Cape Coral FL | 9% | Fresno CA | 4% |
| | New Orleans LA | 7% | El Paso TX | 12% | Riverside-SB CA | 4% |
| | Chicago IL | 7% | Albuquerque NM | 18% | Chicago IL | 4% |
| | Youngstown OH | 8% | Youngstown OH | 18% | Oxnard CA | 5% |
| | Atlanta GA | 9% | Augusta GA | 21% | Youngstown OH | 6% |
| | Fayetteville AR | 11% | Honolulu HI | 25% | Modesto CA | 13% |
| | Honolulu HI | 11% | Daytona Beach FL | 31% | Fayetteville AR | 16% |
| | El Paso TX | 12% | Stockton CA | 60% | Stockton CA | 24% |
| 10 Largest U.S. Metro Areas in order of JOB CENTER Proximity Differential | Boston MA | -3% | New York-Newark NY-NJ | -5% | Boston MA | -8% |
| | Philadelphia PA | -1% | Atlanta GA | -4% | Philadelphia PA | -8% |
| | Miami FL | 1% | Los Angeles CA | -3% | Miami FL | -3% |
| | New York-Newark NY-NJ | 2% | Philadelphia PA | -2% | Atlanta GA | -2% |
| | Dallas-Ft. Worth TX | 2% | Washington DC | -1% | Washington DC | -1% |
| | Los Angeles CA | 3% | Chicago IL | -1% | Dallas-Ft. Worth TX | -1% |
| | Washington DC | 4% | Dallas-Ft. Worth TX | 2% | New York-Newark NY-NJ | -1% |
| | Houston TX | 5% | Miami FL | 3% | Los Angeles CA | 1% |
| | Chicago IL | 7% | Houston TX | 3% | Houston TX | 2% |
| | Atlanta GA | 9% | Boston MA | 4% | Chicago IL | 5% |

Looking beyond averages to atypical cases, the metro areas that appear on particular Top 10 and Bottom 10 proximity lists do so both because of their 2X census tract type and because of the nature of the destination activity. Among 2X African-American tracts, the list of Top 10 job proximity metro areas (those in which residents enjoy unambiguously better job proximity) consists mostly of medium-sized metro areas from across the country. Among 2X Latino tracts, the list of Top 10 metro areas is more slightly tilted toward medium-sized metro areas in the Northeast. Among 2X Poverty tracts, the list of Top 10 metro follows no obvious pattern.

Turning to the three Bottom 10 lists, the places where job centers have unambiguously worse proximity to 2X Black tracts are dominated by large metropolitan areas like Chicago and Atlanta. What these metros have in common is that they have only a few large job centers most of which are fairly distant from predominantly Black neighborhoods. A similar pattern of job-residence segregation is evident among the Bottom 10 list of 2X Latino metros. By contrast, the Bottom 10 job access list for 2X Poverty tracts is dominated by poor metro areas in California's Central Valley (e.g., Stockton, Modesto, and Fresno) and Inland Empire (e.g., Riverside-San Bernardino) regions. These are places in which both jobs and poor households are widely dispersed, making it difficult for workers to easily get to their jobs.

Among the nation's ten largest metro areas, 2X African-American tracts suffer from job proximity disadvantages in all but Philadelphia and Boston. Among the same set of large metro areas, 2X Latino tracts suffer from proximity-to-job center disadvantages in Dallas, Houston, Miami and Boston. By contrast, except for Los Angeles, Chicago, and Houston, 2X Poverty tracts in the nation's ten largest metro areas mostly enjoy proximity-to-job center advantages. Among the exceptions, Los Angeles and Houston are both known for their polycentric urban structure—suggesting that polycentrism may not be a good thing when it comes to helping poor commuters gain easy access to jobs—while in Chicago, the problem is that the poor are disproportionately concentrated in urban neighborhoods immediately south and west of the city. This same pattern was previously observed by Kain in his 1992 commentary on the spatial mismatch hypothesis.

- Hospital Proximity Disparities: Table 4B identifies the metro areas in which the residents of 2X Black, Latino, and Poverty tracts have significantly better and/or worse proximity to nearby hospital facilities. Among 2X African-American tracts (those in which the proportion of African-American residents is twice the metropolitan total), the mean disparity is -6%, meaning that residents of those tracts are six percent closer on average to nearby hospitals than are their counterparts living elsewhere in the same metro area. Put simply, rather than suffering from inferior proximity to local hospitals, the residents of 2X African-American census tracts mostly enjoy superior proximity. At -4.6%, the average hospital proximity advantage for 2X Latino tracts is slightly less pronounced than that of 2X Black tracts. The situation is even better for the residents of 2X Poverty tracts, who, on average, are 13.4% closer to nearby hospitals than are all residents regardless of their poverty status.

The list of Top 10 metro areas in which residents of 2X census tracts enjoy superior hospital proximity—that is, the places where hospital proximity differentials are notably negative—consists mostly of medium-sized

Table 4B: Top 10 and Bottom 10 U.S. Metropolitan Areas based on Race and Poverty-based HOSPITAL Proximity Differentials

| | Proximity Differentials for 2X African-American Tracts | | Proximity Differentials for 2X Latino Tracts | | Proximity Differentials for 2X Poverty Tracts | |
|---|---|---|---|---|---|---|
| All 107 Metropolitan Areas | Average Differential | -6% | Average Differential | -5% | Average Differential | -13% |
| | Median Differential | -2% | Median Differential | -2% | Median Differential | -10% |
| | Differential Std. Dev. | 12% | Differential Std. Dev. | 15% | Differential Std. Dev. | 14% |
| Top 10 Metropolitan Areas in order of HOSPITAL Proximity Advantage | Lakeland FL | -52% | Atlanta GA | -90% | New Haven CT | -54% |
| | Syracuse NY | -40% | New Haven CT | -44% | Syracuse NY | -52% |
| | New Haven CT | -34% | Worcester MA | -43% | Boise ID | -47% |
| | Worcester MA | -32% | Scranton-WB PA | -38% | Scranton-WB PA | -44% |
| | Scranton-WB PA | -32% | Syracuse NY | -34% | Worcester MA | -42% |
| | Albany NY | -32% | Boise ID | -33% | Madison Wi | -41% |
| | Greensboro NC | -26% | Albany NY | -29% | Portland ME | -39% |
| | Des Moines IA | -25% | Lancaster PA | -28% | Providence RI | -39% |
| | Providence RI | -25% | Des Moines IA | -27% | Greensboro NC | -39% |
| | Lancaster PA | -25% | Bridgeport CT | -25% | Grand Rapids MI | -35% |
| Bottom 10 Metropolitan Areas in order of HOSPITAL Proximity Disadvantage | Indianapolis IN | 6% | Winston-Salem NC | 11% | Salt Lake City UT | 0% |
| | Columbus OH | 7% | El Paso TX | 11% | San Antonia TX | 1% |
| | Austin TX | 7% | Richmond VA | 11% | Omaha NE | 1% |
| | Washington DC | 7% | Salt Lake City UT | 11% | San Jose CA | 1% |
| | San Diego CA | 8% | Oxnard CA | 11% | Little Rock AR | 1% |
| | San Antonio CA | 8% | Daytona Beach FL | 13% | Phoenix AZ | 1% |
| | El Paso TX | 10% | Tulsa OK | 16% | Fresno CA | 4% |
| | Stockton CA | 11% | Charleston SC | 19% | Houston TX | 5% |
| | Oxnard CA | 15% | Lakeland FL | 25% | Oxnard CA | 8% |
| | Madison WI | 22% | Bakersfield CA | 27% | Modesto CA | 27% |
| 10 Largest U.S. Metro Areas in order of HOSPITAL Proximity Differential | Philadelphia PA | -6% | Atlanta GA | -90% | Boston MA | -19% |
| | Boston MA | -5% | Boston MA | -9% | Philadelphia PA | -9% |
| | Chicago IL | -2% | Philadelphia PA | -6% | Miami FL | -9% |
| | Miami FL | -1% | Washington DC | -5% | New York-Newark NY-NJ | -3% |
| | New York-Newark NY-NJ | -1% | New York-Newark NY-NJ | -1% | Atlanta GA | -3% |
| | Dallas-Ft. Worth TX | 2% | Chicago IL | 2% | Los Angeles CA | -2% |
| | Atlanta GA | 3% | Los Angeles CA | 2% | Chicago IL | -2% |
| | Los Angeles CA | 5% | Miami FL | 4% | Dallas-Ft. Worth TX | -2% |
| | Houston TX | 5% | Houston TX | 5% | Washington DC | 0% |
| | Washington DC | 7% | Dallas-Ft. Worth TX | 6% | Houston TX | 5% |

## Table 4C: Top 10 and Bottom 10 U.S. Metropolitan Areas based on Race and Poverty-based DAY CARE Proximity Differentials

| | Proximity Differentials for 2X African-American Tracts | | Proximity Differentials for 2X Latino Tracts | | Proximity Differentials for 2X Poverty Tracts | |
|---|---|---|---|---|---|---|
| All 107 Metropolitan Areas | Average Differential | -35% | Average Differential | -27% | Average Differential | -36% |
| | Median Differential | -41% | Median Differential | -32% | Median Differential | -43% |
| | Differential Std. Dev. | 30% | Differential Std. Dev. | 33% | Differential Std. Dev. | 44% |
| Top 10 Metropolitan Areas in order of DAY CARE Proximity Advantage | Louisville KY | -73% | Riverside CA | -78% | Albany NY | -70% |
| | Jackson MS | -69% | Rochester NY | -76% | Lancaster PA | -69% |
| | Rochester NY | -67% | Santa Rosa CA | -74% | Bakersfield CA | -66% |
| | Albany NY | -66% | Lancaster PA | -72% | Syracuse NY | -66% |
| | Birmingham AL | -65% | San Antonio TX | -65% | Scranton–Wilkes B. PA | -66% |
| | Baton Rouge LA | -65% | Springfield MA | -61% | Birmingham AL | -66% |
| | Lancaster PA | -65% | Allentown PA | -61% | Baton Rouge LA | -65% |
| | Chattanooga TN | -64% | Albany NY | -60% | Palm Bay FL | -65% |
| | Syracuse NY | -63% | Scranton–WB PA | -59% | Fayetteville AR | -64% |
| | Harrisburg PA | -62% | Boise ID | -58% | Lexington KY | -64% |
| Bottom 10 Metropolitan Areas in order of Day Care Proximity Disadvantage | Austin TX | 6% | Milwaukee WI | 13% | Spokane WA | -2% |
| | Madison WI | 7% | Modesto CA | 14% | Phoenix AZ | 1% |
| | McAllen TX | 7% | McAllen TX | 17% | Santa Rosa CA | 8% |
| | Boise City ID | 14% | Augusta GA | 20% | Milwaukee WI | 32% |
| | Honolulu HI | 14% | Austin TX | 40% | New Orleans LA | 35% |
| | New Orleans LA | 16% | Lakeland FL | 45% | Madison WI | 37% |
| | Spokane WA | 20% | El Paso TX | 46% | El Paso TX | 43% |
| | Milwaukee WI | 24% | Honolulu HI | 50% | Austin TX | 54% |
| | Bakersfield CA | 36% | Spokane WA | 52% | Albuquerque NM | 54% |
| | Oxnard CA | 165% | Fresno CA | 189% | McAllen TX | 335% |
| 10 Largest U.S. Metro Areas in order of Day Care Proximity Differential | Philadelphia PA | -56% | New York-Newark NY-NJ | -51% | New York-Newark NY-NJ | -63% |
| | New York-Newark NY-NJ | -55% | Boston MA | -47% | Philadelphia PA | -58% |
| | Boston MA | -42% | Miami FL | -41% | Boston MA | -52% |
| | Atlanta GA | -39% | Washington DC | -35% | Atlanta GA | -46% |
| | Chicago IL | -39% | Atlanta GA | -31% | Washington DC | -45% |
| | Miami FL | -34% | Philadelphia PA | -30% | Chicago IL | -43% |
| | Houston TX | -34% | Chicago IL | -28% | Miami FL | -39% |
| | Washington DC | -26% | Los Angeles CA | -24% | Houston TX | -31% |
| | Dallas-Ft. Worth TX | -22% | Houston TX | -21% | Los Angeles CA | -25% |
| | Los Angeles CA | -21% | Dallas-Ft. Worth TX | -18% | Dallas-Ft. Worth TX | -10% |

metro areas in the Northeast. While more diverse in terms of age and size, the Bottom 10 hospital proximity metro areas list (those with inferior levels of hospital proximity) tilts toward faster-growing metro areas in the South and West. This is especially true for 2X African-American and Latino tracts. Among very large metropolitan areas, Washington, D.C., San Diego, San Antonio, and Houston all stand out for their deficient hospital proximity to at least one 2X neighborhood type.

Among the ten largest metropolitan areas, New York, Philadelphia and Boston, all of which are known nationally as health care centers, also offer hospital proximity benefits to residents of their 2X Black, Latino, and Poverty tracts. By contrast, and alone among the ten largest metro areas, Houston consistently disadvantages its 2X Black, Latino, and Poverty tracts in terms of hospital proximity. Residents of Washington D.C.'s 2X African-American tracts also suffer notable hospital proximity disadvantages. Washington's hospital facilities are mostly clustered in the region's western and northern counties, while its Black population is disproportionately located in the south and east.

Day Care Proximity Disparities: Table 4C identifies the metro areas in which the residents of 2X Black, Latino, and Poverty tracts must travel longer and shorter distances to the five nearestday care facilities. Among 2X Black tracts (those in which the proportion of African-American residents is twice the metropolitan total), the mean proximity disparity is -34.7%, meaning that residents of those tracts are nearly 35 percent closer to nearby day care facilities than are other residents of the same metropolitan area.

At -25.6%, the average day care proximity advantage for 2X Latino tracts is also sizeable, although slightly less than that of 2X Black tracts. The average day care proximity advantage for residents of 2X Poverty tracts is comparable to that of 2X Black tracts. The fact that the median differential is greater than the average differential for all three 2X tract types suggests even greater day care proximity advantages.

The three lists of Top 10 day care metro areas (for which residents of 2X census tracts are much closer to the three nearest day care facilities) mostly consists of small and medium-sized metro areas. Lancaster (Pennsylvania) and Albany (New York) appear on all three Top 10 day care proximity lists, while Baton Rouge, Birmingham, and Rochester (New York) appear on two. The only very large metro area to appear on a 2X Top 10 day care list is Riverside-San Bernardino.

The Bottom 10 lists of 2X day care metros—those metros in which residents of 2X Black, Latino, and Poverty tracts must travel longer-than-average distances to get to nearby day care facilities—is more diverse in terms of size and includes such large metro areas as Austin and Phoenix. Austin, somewhat surprisingly, appears on all three Bottom 10 day care lists, as do Milwaukee, McAllen, and Spokane. Three other metro areas, Madison, Honolulu, and New Orleans appear on two Bottom 10 day care lists. While it might be tempting to connect day care access disparities to inter-metropolitan differences in racial segregation levels—Milwaukee, for example, which appears prominently on all three Bottom 10 day care lists is among the most segregated metro areas in the nation—a closer look reveals this not to be the case. Nor do day care access differentials appear to correspond to inter-metropolitan differences in income. Among individual states, Texas and California include metro areas on both Top 10 and Bottom 10 day care access lists, suggesting that state and local day care licensing laws play some role in accounting for day care access disparities.

Residents of 2X Black, Latino, and Poverty tracts in the country's ten largest metro areas enjoy consistently better access to nearby day care facilities than do residents of other tracts. In the New York City-Newark metro area, this advantage approaches 50%! Given these large differentials, it is worth reiterating that we are only considering proximity, and that many other factors, most notably price, reputation, and the availability of open slots shape parents' decisions about where to send their kids for day care. The degree to which the proximity advantages of day care in the nation's largest metros are favorably or unfavorably matched by these other attributes, especially for poor and minority parents, needs much more study.

- <u>Public Park Proximity Disparities:</u> Table 4D identifies the metro areas in which residents of 2X Black, Latino, and Poverty tracts travel much longer and much shorter distances to the nearest public park. Among 2X Black tracts (those in which the proportion of African-American residents is twice the metropolitan total), the mean access differential is -37.2%, meaning that residents of those tracts are 37.2 percent closer to the nearest public park than the typical metro area resident. The residents of 2X Latino tracts are 29.3% closer on average to the nearest public park, while residents of 2X Poverty tracts are 39% closer. As with day care facilities, median park access differentials are larger than mean differentials, meaning that parks are even closer to most residents of poverty and minority tracts than is indicated by the average value. This does not mean that every African-American, Latino, or poor metropolitan resident lives closer to a neighborhood park than does their white or upper-income counterpart. It means rather that minority and poor households are not systematically disadvantaged when it comes to park access.

Turning to the Top 10 and Bottom 10 groupings, among 2X Black and Poverty census tracts, the lists of Top 10 park proximity metro areas are dominated by medium-sized metro areas in the Southeast and New York State. Residents of minority and poverty tracts in these metro areas enjoy better proximity to nearby parks than do residents of other tracts. This superior level of park proximity is due to a combination of smaller geographic size (which makes everything closer) and a bias toward providing more neighborhood parks. Among 2X Latino tracts, the Top 10 park proximity list includes El Paso and Riverside-San Bernardino, two metro areas with large Latino populations. The El Paso metro area also appears on the Bottom 10 list of park access for 2X Black census tracts, as does Phoenix. Honolulu appears on the Bottom 10 lists for both 2X Black and 2X Latino tracts. These results mostly reflect differences in residential segregation patterns between African-Americans and Latinos. In Riverside-San Bernardino, for example, Black residents are concentrated in just a few neighborhoods (which mostly lack park proximity) while Latinos are more widely distributed throughout the metropolitan area. A similar pattern is

Table 4D: Top 10 and Bottom 10 U.S. Metropolitan Areas based on Race and Poverty-based PARK Proximity Differentials

| | Proximity Differentials for 2X African-American Tracts | | Proximity Differentials for 2X Latino Tracts | | Proximity Differentials for 2X Poverty Tracts | |
|---|---|---|---|---|---|---|
| All 107 Metropolitan Areas | Average Differential | -37% | Average Differential | -31% | Average Differential | -39% |
| | Median Differential | -45% | Median Differential | -37% | Median Differential | -45% |
| | Differential Std. Dev. | 39% | Differential Std. Dev. | 43% | Differential Std. Dev. | 38% |
| Top 10 Metropolitan Areas in order of PARK Proximity Advantage | Birmingham AL | -83% | Albuquerque NM | -76% | Baton Rouge LA | -82% |
| | Portland ME | -83% | Grand Rapids MI | -75% | Birmingham AL | -79% |
| | Louisville KY | -76% | San Antonio TX | -74% | Albany NY | -78% |
| | Tulsa OK | -75% | Tulsa OK | -72% | Louisville KY | -78% |
| | Greensboro NC | -74% | Riverside CA | -70% | Knoxville TN | -74% |
| | Syracuse NY | -73% | Providence RI | -69% | Greensboro NC | -74% |
| | Baton Rouge LA | -72% | Portland ME | -68% | Tulsa OK | -74% |
| | Jackson MS | -72% | Omaha NE | -67% | Syracuse NY | -72% |
| | Memphis TN | -71% | Allentown PA | -66% | Colorado Springs CO | -72% |
| | Albuquerque NM | -70% | Colorado Springs CO | -66% | San Antonio TX | -70% |
| Bottom 10 Metropolitan Areas in order of PARK Proximity Disadvantage | Riverside CA | -1% | Baton Rouge LA | -2% | Dallas TX | -6% |
| | Phoenix AZ | 3% | Columbia SC | -2% | Los Angeles CA | -1% |
| | Charleston SC | 12% | North Port FL | -1% | New Orleans LA | 1% |
| | Augusta GA | 21% | El Paso TX | 27% | Augusta GA | 12% |
| | Lancaster PA | 22% | Lancaster PA | 30% | Santa Rosa CA | 14% |
| | Raleigh NC | 31% | Birmingham AL | 42% | Austin TX | 20% |
| | Bakersfield CA | 36% | Austin TX | 66% | Lancaster PA | 22% |
| | El Paso TX | 38% | Honolulu HI | 70% | Raleigh NC | 27% |
| | Honolulu HI | 50% | Palm Bay FL | 80% | El Paso TX | 41% |
| | Palm Bay FL | 65% | Durham NC | 87% | Albuquerque NM | 70% |
| 10 Largest U.S. Metro Areas in order of PARK Proximity Differential | Boston MA | -56% | Boston MA | -59% | Boston MA | -57% |
| | Atlanta GA | -53% | Houston TX | -56% | Philadelphia PA | -51% |
| | Philadelphia PA | -50% | Washington DC | -51% | Houston TX | -44% |
| | Dallas-Ft. Worth TX | -40% | Dallas-Ft. Worth TX | -50% | Atlanta GA | -44% |
| | Washington DC | -33% | New York-Newark NY-NJ | -40% | New York-Newark NY-NJ | -40% |
| | Houston TX | -30% | Miami FL | -39% | Washington DC | -38% |
| | New York-Newark NY-NJ | -28% | Philadelphia PA | -37% | Chicago IL | -25% |
| | Chicago IL | -22% | Atlanta GA | -25% | Miami FL | -16% |
| | Miami FL | -12% | Chicago IL | -24% | Dallas-Ft. Worth TX | -6% |
| | Los Angeles CA | -2% | Los Angeles CA | -12% | Los Angeles CA | -1% |

## Table 4E: Top 10 and Bottom 10 U.S. Metropolitan Areas based on Race and Poverty-based LIBRARY Proximity Differentials

| | Proximity Differentials for 2X African-American Tracts | | Proximity Differentials for 2X Latino Tracts | | Proximity Differentials for 2X Poverty Tracts | |
|---|---|---|---|---|---|---|
| All 107 Metropolitan Areas | Average Differential | -26% | Average Differential | -24% | Average Differential | -35% |
| | Median Differential | -29% | Median Differential | -26% | Median Differential | -40% |
| | Differential Std. Dev. | 23% | Differential Std. Dev. | 21% | Differential Std. Dev. | 40% |
| Top 10 Metropolitan Areas in order of LIBRARY Proximity Advantage | Scranton–WB PA | -95% | Riverside CA | -71% | Syracuse NY | -64% |
| | Syracuse NY | -64% | Bakersfield CA | -57% | Albany NY | -63% |
| | Albany NY | -57% | Oxnard CA | -57% | Boise City ID | -62% |
| | Jackson MS | -56% | Lancaster PA | -54% | Scranton–W.Barre PA | -61% |
| | Pittsburgh PA | -55% | Providence RI | -50% | Fayetteville AR | -56% |
| | Rochester NY | -52% | Modesto CA | -50% | Pittsburgh PA | -56% |
| | Birmingham AL | -50% | Grand Rapids MI | -48% | Lexington KY | -55% |
| | Louisville KY | -50% | Rochester NY | -48% | Deltona FL | -55% |
| | Knoxville TN | -48% | Hartford CT | -46% | Allentown PA | -55% |
| | Philadelphia PA | -48% | Chattanooga TN | -44% | Birmingham AL | -55% |
| Bottom 10 Metropolitan Areas in order of LIBRARY Proximity Disadvantage | Charleston SC | -5% | Palm Bay FL | -1% | Dayton OH | -21% |
| | Las Vegas NV | -1% | Madison WI | 4% | Des Moines IA | -19% |
| | Palm Bay FL | 1% | Deltona FL | 5% | Tampa FL | -19% |
| | El Paso TX | 6% | Virginia Beach VA | 5% | Phoenix AZ | -17% |
| | Worcester MA | 10% | Augusta GA | 6% | Honolulu HI | -15% |
| | Provo UT | 10% | Austin TX | 7% | New Orleans LA | -3% |
| | Modesto CA | 11% | Cape Coral FL | 11% | Albuquerque NM | 10% |
| | Riverside CA | 21% | Lakeland FL | 21% | El Paso TX | 11% |
| | Honolulu HI | 25% | Honolulu HI | 44% | Austin TX | 22% |
| | Oxnard CA | 127% | Fresno CA | 92% | McAllen TX | 341% |
| 10 Largest U.S. Metro Areas in order of LIBRARY Proximity Differential | Philadelphia PA | -48% | Houston TX | -42% | Philadelphia PA | -52% |
| | New York-Newark NY-NJ | -39% | New York-Newark NY-NJ | -39% | New York-Newark NY-NJ | -45% |
| | Boston MA | -34% | Los Angeles CA | -35% | Boston MA | -42% |
| | Chicago IL | -31% | Philadelphia PA | -33% | Washington DC | -42% |
| | Atlanta GA | -25% | Boston MA | -33% | Atlanta GA | -42% |
| | Miami FL | -20% | Dallas-Ft. Worth TX | -31% | Houston TX | -38% |
| | Houston TX | -20% | Washington DC | -30% | Chicago IL | -37% |
| | Washington DC | -17% | Miami FL | -29% | Los Angeles CA | -26% |
| | Dallas-Ft. Worth TX | -16% | Chicago IL | -29% | Dallas-Ft. Worth TX | -23% |
| | Los Angeles CA | -12% | Atlanta GA | -12% | Miami FL | -22% |

evident among the Bottom 10 list of 2X Poverty tracts: the metro areas on this list are highly segregated by income, with poorer households living in neighborhoods that typically lack park proximity. This pattern is more evident in Texas and California.

Most very large metro areas consist of dozens (and in some cases, hundreds) of municipalities, each one of which typically has one or more public parks. This is why all of the ten largest U.S. metro areas score well when it comes to providing superior park access for the residents of their 2X Black, Latino, and Poverty tracts. In the cases of Boston and Philadelphia, these proximity advantages are on the order of 40 percent or more! Residents of 2X Black and Poverty tracts in Atlanta also enjoy 40+ percent park proximity advantages, as do residents of 2X Latino tracts in Houston. The only very large metropolitan area in which residents of the various 2X tracts do not enjoy consistent park proximity advantages (compared to other residents) is Los Angeles. This is not because 2X tract residents suffer from inferior park access, but rather because local public parks are so plentiful and widely distributed across the Los Angeles region that no group or location can be said to have better (or worse) park access.

- Library Proximity Disparities: Table 4E identifies the ten top and bottom metro areas in which residents of 2X Black, Latino, and Poverty tracts travel shorter and longer distances, respectively, to get to their nearest public library. Among residents of 2X Black tracts (those in which the proportion of African-American residents is twice the metropolitan total), the average distance differential is -26%, meaning that residents of those tracts are 26 percent closer to the nearest library than are residents of other census tracts in the same metro area. The residents of 2X Latino tracts are, on average, 24% closer to their nearest library, and the residents of 2X Poverty tracts are 35% closer. As previously caveated, these results cannot be interpreted as meaning that every African-American, Latino, or poor household lives near a public library. What they do mean is that urban residents living in poor neighborhoods should not, by and large, be regarded as being systematically disadvantaged when it comes to library access.

  Among 2X Black census tracts, the list of Top 10 metro areas in terms of library proximity is dominated by medium-sized metros in Pennsylvania and New York. With funding help from industrialist Andrew Carnegie, both states undertook major statewide library building efforts at the turn of the 20th Century, and the effects of those efforts are still being felt a century later. Pennsylvania and New York also dominate the list of Top 10 metro area for library proximity to 2X Poverty census tracts. Among 2X Latino tracts, the list of Top 10 metro areas tilts toward metro areas in California with large Latino populations, as well as to medium-sized Northeast metro areas like Providence where Latino residents are concentrated in inner urban neighborhoods.

  The three Bottom 10 lists for library proximity are mostly dominated by fast-growing metro areas in California and the West (2x Black census tracts), by fast-growing metro areas in the Southeast (2x Latino tracts), and by metro areas in Texas (2x Poverty tracts). In addition to being fast-growing, the metro areas on the three Bottom 10 library lists are more suburban in character, with either small or widely dispersed minority and poverty populations.

As with parks, superior library proximity is partly a function of metro area size, with residents of 2X Black, Latino, and Poverty census tracts in the nation's ten largest metro all living closer, on average, to their nearest library than other metro area residents. Among these very large metro areas, Philadelphia, New York City, and Boston are consistently at the top of the library proximity heap, while Dallas-Ft. Worth and Miami tend to be closer to the bottom. Chicago and Atlanta score well in terms of library access for residents of 2X Black tracts, but not so well for residents of 2X Latino tracts. Los Angeles, by contrast, scores well for 2X Latino neighborhoods but less well for 2X Black tracts. As with parks, these results are mostly a function of how the different 2X tract types are spatially distributed. 2X Latino tracts, for example, are widely distributed across the Los Angeles region, resulting in that metro area having a high proximity ranking for 2X Latino tracts and public libraries.

We undertook this paper assuming that our findings would support what has long been the conventional wisdom: that minority and poor households suffer from deep and systematic disadvantages when in terms of their proximity to many everyday activities. What we found is exactly the opposite: with very few exceptions, households living in census tracts with double (or more) the metro area-wide share of Black, Latino, and poor households live consistently closer to regional job centers, to nearby hospitals, and day care centers, and to parks and libraries that do residents of Whiter and wealthier neighborhoods. In some places, this occurs as a result of where people live. In others, it is due to the spatial distribution of the different destination activities.

This finding is not the result of a few metro areas with better opportunity proximity pulling up overall averages. In all almost every combination of activity and 2X tract type, the median differentials are larger than the mean differential. This indicates that the access benefits enjoyed by the residents of 2X Black, Latino, and Poverty census tracts are broadly-based and not limited to just a few neighborhoods and metropolitan areas.

This is not to say that every African-American or Latino or poor resident of a major metropolitan area enjoys superior job, hospital, day care, park, or library proximity. Nor is it to say that the quality of the job or service at the destination trip end is equal to that enjoyed by the residents of predominantly White and middle-class neighborhoods. What it does suggest, and rather convincingly so, is that when proximity is measured as distance rather than travel time, poor and minority neighborhoods do not suffer from systematic travel access disparities. To the extent that such disparities do exist, they are more likely to be found on the mobility side of the travel equity equation. This is where we turn next.

# III. CARLESSNESS DISPARITIES

Our approach to characterizing mobility disparities is more basic than our approach to identifying accessibility disparities. Very simply, we identify households as being mobility-disadvantaged if they lack at least one privately-owned motorized vehicle. For most U.S. households, this vehicle is a car. This criterion is very much a North American one. Compared to urban areas in Europe, Latin-America, and most parts of Asia, U.S. metropolitan areas are distinguished by their low residential densities, by their multi-centric urban spatial structure, by their lack of comprehensive public transport options, and by their high level of auto ownership. There are a handful of communities in the U.S. where it is possible to live quite comfortably without owning a car, but these are most limited to core area neighborhoods in high-density cities like New York, Philadelphia, Chicago, Boston, and San Francisco. These oases of walkability notwithstanding, there are no U.S. metro areas in which residents who do not have access to a car can be said to have comparable level of metropolitan mobility to those who do. Recent efforts to expand public transit service notwithstanding, among U.S. metro areas with a half-million population or more, the current national rate of carlessness stands at just 3.7 percent.

With the rise of economical ride-hailing services such as Uber and Lyft, the distinctions between auto ownership, auto availability, and automobility may be widening especially in urban neighborhoods served by public transit. Depending on where they live, an increasing number of households are finding that they don't need to own a car in order to enjoy some level of automobility (Brown 2017). In other locations and situations, the availability of ride-hailing services is reducing the need for a second car. This expanded choice set is already showing up in national auto-ownership statistics, albeit on a small scale. According to the Census Bureau, the national share of carless households, after bottoming-out at a rate of 3.2 percent in 2013, has since risen by 0.5 percent. While some analysts attribute this rise to the Millennial generation's disenchantment with driving and the dominant car culture (Garikapati et al., 2017; McDonald, 2016), others look to the growing use of Uber and Lyft (Brown, 2018; Grahn et al., 2019).

Table 5 identifies the share of carless households in each of the 107 metro areas included in this study. For the sample as a whole, the average share of households lacking daily access to a car is 3.7 percent, the same as the national rate. Among individual metro areas, the share of carless households varies from a high of 22.6 percent in the New York City-Newark metro area to a low of zero percent in McAllen, Texas and all three of Utah's major metro areas.[8]

Table 6 identifies those metro areas with the largest and smallest disparities between the overall rate of carlessness and the rate in 2X African-American, 2X Latino, and 2X Poverty census tracts. A complete listing of carlessness disparities is provided in Appendix D.

Among 2X African-American tracts, the average carlessness rate differential is 4.0 percent, meaning that the share of carless households among 2X African-American tracts is four percentage points higher than the share of carless households in the metro area as whole. Among 2X Latino tracts, the average carlessness rate differential is 1.5 percent. Among 2X Poverty tracts, it is 6.7 percent higher. To the degree that access to a car is a reliable measure of mobility, then on average, residents of 2X Poverty tracts have significantly less mobility than their counterparts elsewhere in the same

| Table 5: 2017 Share of Carless Households by Metropolitan Area | |
|---|---|
| **All 107 Metropolitan Areas** | |
| Average Carless Share | 3.7% |
| Median Carless Share | 3.4% |
| Standard Deviation | 2.5% |

| Metro Area | Carless Share | Metro Area | Carless Share | Metro Area | Carless Share |
|---|---|---|---|---|---|
| New York-Newark NY-NJ | 22.6% | Louisville KY | 4.0% | Bakersfield CA | 2.8% |
| Boston MA | 8.6% | Atlanta GA | 4.0% | Portland ME | 2.8% |
| Lancaster PA | 7.6% | Miami FL | 4.0% | Birmingham AL | 2.8% |
| Chicago IL | 7.6% | Los Angeles-Long Beach CA | 3.9% | Sacramento CA | 2.7% |
| Philadelphia PA | 7.5% | Tucson AZ | 3.8% | Stockton CA | 2.7% |
| Syracuse NY | 7.2% | Akron OH | 3.8% | Charleston SC | 2.7% |
| Baltimore MD | 7.2% | Jacksonville FL | 3.8% | Modesto CA | 2.7% |
| New Orleans LA | 7.1% | Fresno CA | 3.7% | Jackson MS | 2.7% |
| San Francisco CA | 7.0% | Seattle WA | 3.7% | Omaha NE | 2.6% |
| Buffalo NY | 6.6% | Dayton OH | 3.7% | Denver CO | 2.5% |
| Rochester NY | 6.1% | Portland OR | 3.7% | Oklahoma City OK | 2.5% |
| New Haven CT | 6.0% | Columbus OH | 3.6% | Cape Coral FL | 2.4% |
| Cleveland OH | 6.0% | Indianapolis IN | 3.6% | Tulsa OK | 2.3% |
| Pittsburgh PA | 6.0% | Virginia Beach VA | 3.5% | San Diego CA | 2.3% |
| Milwaukee WI | 5.9% | Minneapolis-St. Paul MN | 3.4% | Albuquerque NM | 2.3% |
| Washington D.C. | 5.4% | Augusta GA | 3.4% | Nashville TN | 2.2% |
| Albany NY | 5.4% | Lexington KY | 3.4% | Des Moines IA | 2.2% |
| Madison WI | 5.3% | Chattanooga TN | 3.4% | San Jose CA | 2.2% |
| Hartford CT | 5.2% | Baton Rouge LA | 3.3% | Raleigh NC | 2.2% |
| Toledo OH | 4.9% | Lakeland FL | 3.2% | Colorado Springs CO | 2.1% |
| Detroit MI | 4.8% | El Paso TX | 3.2% | Fayetteville AR | 2.1% |
| Honolulu HI | 4.7% | Little Rock AR | 3.2% | Riverside CA | 2.0% |
| Springfield MA | 4.7% | Tampa FL | 3.2% | Santa Rosa CA | 1.8% |
| Las Vegas NV | 4.7% | Richmond VA | 3.1% | Knoxville TN | 1.8% |
| Harrisburg PA | 4.7% | San Antonio TX | 3.1% | Boise City IA | 1.7% |
| Memphis TN | 4.6% | Phoenix AZ | 3.1% | North Port FL | 1.7% |
| St. Louis MO | 4.5% | Kansas City KS | 3.0% | Dallas-Ft. Worth TX | 1.7% |
| Cincinnati OH | 4.5% | Spokane WA | 3.0% | Oxnard CA | 1.4% |
| Providence RI | 4.4% | Palm Bay FL | 2.9% | Wichita KS | 0.1% |
| Durham NC | 4.3% | Grand Rapids MI | 2.9% | Houston TX | 0.1% |
| Worcester MA | 4.3% | Deltona FL | 2.9% | Austin TX | 0.1% |
| Winston NC | 4.3% | Columbia SC | 2.9% | Salt Lake City UT | 0.0% |
| Bridgeport CT | 4.1% | Orlando FL | 2.9% | McAllen TX | 0.0% |
| Allentown PA | 4.1% | Charlotte NC | 2.8% | Ogden UT | 0.0% |
| Scranton–Wilkes PA | 4.1% | Greensboro NC | 2.8% | Provo UT | 0.0% |
| Youngstown OH | 4.0% | Greenville SC | 2.8% | | |
| *(continued next column)* | | *(continued next column)* | | | |

Table 6: Top 10 and Bottom 10 U.S. Metropolitan Areas based on Carless Rate Differentials Between 2X Minority and Poverty Census Tracts and All Tracts

| | Carless Rate Differential for 2X African-American Tracts | | Carless Rate Differential for 2X Latino Tracts | | Carless Rate Differential for 2X Poverty Tracts | |
|---|---|---|---|---|---|---|
| All 107 Metropolitan Areas | Average Differential | 4.0% | Average Differential | 2.0% | Average Differential | 6.7% |
| | Median Differential | 3.5% | Median Differential | 1.1% | Median Differential | 6.2% |
| | Differential Std. Dev. | 3.3% | Differential Std. Dev. | 3.6% | Differential Std. Dev. | 4.2% |
| Ten Metro Areas with the LARGEST Carlessness Rate Differentials between 2X Census Tracts and the Entire Metro Area | Syracuse NY | 13% | New York-Newark NY-NJ | 18% | New York-Newark NY-NJ | 27% |
| | Philadelphia PA | 13% | Harrisburg PA | 15% | Madison WI | 18% |
| | Baltimore MD | 12% | Syracuse NY | 13% | Philadelphia PA | 16% |
| | Albany NY | 11% | Philadelphia PA | 10% | Baltimore MD | 16% |
| | Buffalo NY | 11% | Hartford CT | 9% | Syracuse NY | 14% |
| | New York-Newark NY-NJ | 11% | Albany NY | 9% | New Orleans LA | 14% |
| | Rochester NY | 10% | Allentown PA | 9% | Boston MA | 14% |
| | Pittsburgh PA | 10% | Rochester NY | 9% | El Paso TX | 14% |
| | Louisville KY | 10% | Springfield MA | 9% | Washington D.C. | 12% |
| | Richmond VA | 8% | Bridgeport CT | 8% | Pittsburgh PA | 12% |
| Ten Metro Areas with the SMALLEST Carlessness Rate Differentials between 2X Census Tracts and the Entire Metro Area | Provo UT | 0% | Deltona FL | -1% | Santa Rosa CA | 2% |
| | El Paso TX | 0% | New Orleans LA | -1% | Boise ID | 2% |
| | Santa Rosa CA | 0% | Memphis TN | -1% | Oxnard CA | 2% |
| | Houston TX | 0% | Richmond VA | -1% | Modesto CA | 1% |
| | Boise ID | 0% | San Francisco CA | -2% | Salt Lake City UT | 0% |
| | Modesto CA | 0% | Augusta GA | -2% | McAllen TX | 0% |
| | Honolulu HI | 0% | Fresno CA | -2% | Ogden UT | 0% |
| | Oxnard CA | 0% | Honolulu HI | -3% | Provo-Orem UT | 0% |
| | Madison WI | -2% | San Antonio TX | -3% | Houston TX | 0% |
| | Milwaukee WI | -4% | Baltimore MD | -4% | Austin TX | 0% |
| 2X Carlessness Rate Differentials in the 10 Largest US Metro Areas | Philadelphia PA | 13% | New York-Newark NY-NJ | 18% | New York-Newark NY-NJ | 27% |
| | Chicago IL | 8% | Philadelphia PA | 10% | Philadelphia PA | 16% |
| | New York-Newark NY-NJ | 7% | Boston MA | 7% | Boston MA | 14% |
| | Washington DC | 6% | Los Angeles CA | 2% | Washington DC | 12% |
| | Atlanta GA | 5% | Atlanta GA | 2% | Chicago IL | 10% |
| | Miami FL | 3% | Dallas-Ft. Worth TX | 1% | Los Angeles CA | 8% |
| | Dallas-Ft. Worth TX | 2% | Miami FL | 0% | Atlanta GA | 8% |
| | Los Angeles CA | 2% | Washington DC | 0% | Miami FL | 7% |
| | Houston TX | 0% | Chicago IL | -1% | Dallas-Ft. Worth TX | 5% |
| | Boston MA | 0% | Houston TX | -2% | Houston TX | 0% |

metropolitan area. Residents of 2X African-American tracts have moderately less mobility, and residents of 2X Latino tracts have modestly less mobility.

These differentials vary widely by metropolitan area. Residents of 2X Black tracts in Syracuse, Philadelphia, Baltimore, Albany, Buffalo, and New York-Newark must contend with much reduced mobility when compared with residents of other census tracts. In Milwaukee, by contrast (and only in Milwaukee) rates of carlessness in 2X Black census tracts are notably lower than overall rates.

Residents of 2X Latino census tracts in New York City-Newark, Harrisburg, Syracuse, and Philadelphia also face large mobility disadvantages when compared to residents of other census tracts in the same region. By contrast, residents of 2X Latino neighborhoods in Pittsburgh, Springfield (Massachusetts), Baltimore, and Allentown have lower rates of carlessness than residents of other tracts in the same metro areas. Residents of 2X Poverty tracts face larger mobility disparities than residents of 2X Black and Latino tracts. In the New York City-Newark metro area, for example, the average rate of carlessness in 2X Poverty tracts is 49.4 percent! This is a whopping 26.8 percent higher than the rate of household carlessness elsewhere in the New York City region. Other metro areas in which residents of 2X Poverty tracts suffer from large mobility disparities include Madison, Philadelphia, Baltimore, Syracuse, New Orleans, Boston, El Paso, Washington, D.C., and Pittsburgh. By contrast, there are no U.S. metropolitan areas in which the residents of 2X Poverty tracts suffer from lower rates of carlessness than for their metropolitan areas.

Three metro areas, Syracuse, Philadelphia, and New York City-Newark appear on all three sets of Top 10 carlessness disparity lists, while another four, Baltimore, Albany, Rochester, and Pittsburg appear on two disparity lists. Among the metro areas where residents of 2X Black, Latino, and Poverty tracts have systematically better automobility are Santa Rosa, Boise, Oxnard, Modesto, Honolulu, and Houston.

Among the nation's ten largest metro areas, the mobility disparity picture is a mirror image of the proximity picture. Residents of 2X tracts in the nation's largest metro areas have uniformly better proximity to jobs and services (when compared to other metro area residents), but in terms of mobility, the same 2X residents suffer from much higher rates of carlessness. We conjecture that this is principally because of the much higher costs of owning and parking a car in large cities and metro areas.

Among residents of 2X Black neighborhoods, these disparities are widest in Philadelphia, Chicago, and New York City, and narrowest in Houston and Boston. Among residents of 2X Latino neighborhoods, they are widest in New York, Philadelphia and Boston. In Houston, by contrast, residents of 2X Latino neighborhoods suffer from slightly lower rates of carlessness. The New York City, Philadelphia, and Boston also top the list of metro areas with the widest carlessness disparities among residents of 2X Poverty neighborhoods.

These results do not imply that all poor and minority residents of large metro areas have lower mobility levels. As noted previously, we did not consider the quality and availability of public transportation services, which are generally better in larger metro areas than in smaller ones. Nor did we explicitly consider other factors which influence local rates of car ownership, including household structure, unemployment rates, automobile ownership costs, and urban form.

Neighborhood-level built form factors regularly combine with residential self-selection biases in ways that influence the household decisions to own a car (Huang et al., 2017; Cao et al., 2007). Among lower-density metro areas in the South and West, residents of poor and minority neighborhoods are much more likely to own and regularly use a car. If those same residents were to move to the Northeast or Midwest, where, depending on the metro area, public transit service is generally better, they would be less likely to want or own a car (Glaeser et al., 2008).

## IV. WORST-CASE OUTCOMES

Having first identified metro areas in which residents of minority and poor census tracts suffer from reduced proximity to jobs, hospitals, day care, and other urban services; and then identified metro areas where these same residents suffer from heightened carlessness, we now combine the two sets of listings. This was accomplished by developing separate proximity and mobility rankings for each combination of activity type (e.g., job centers, hospitals, day care, parks, and libraries) and 2X census tract type (e.g., 2X African-American tracts, 2X Latino tracts, and 2X Poverty tracts), and then identifying those metro areas falling 0.5 standard deviations below the average proximity and mobility value for each activity type and 2X tract type combination. The resulting list of "low proximity, low mobility, worst-case" metro areas is presented in Table 7 for each combination of activity type and 2X tract type. These are the "outlier" metro areas in which the residents of 2X Black, Latino, and Poverty census tracts suffer from extremely poor activity proximity and from extremely high rates of carlessness. These are the metro areas where those who are the most socio-economically vulnerable are also the most transportation disadvantaged.

Starting in the upper left-hand corner of Table 7, the list of metropolitan areas in which the residents of 2X Black census tracts suffer both from greatly reduced job proximity and automobility include New York City-Newark, Chicago, Washington, D.C., St. Louis, Pittsburgh, Cleveland, Richmond, Louisville, and New Orleans. As a group, these metro areas all have large African-American populations, high poverty rates, and monocentric urban forms. Except for Washington, DC, all are former manufacturing centers, and except for New

Orleans and Louisville, all are in the Northeast or Midwest. New York, Chicago, and Washington D.C. have extensive urban rail systems, but the others rely on buses to meet their mass transit needs. Five of the metro areas on this list (New York-Newark, Chicago, Washington, DC, St. Louis, and Louisville) also appear on the list of job proximity worst-case metros for residents of 2X Poverty tracts.

With the exception of Norfolk/Virginia Beach, all the metro areas on the list of worst-case job proximity places for residents of 2X Poverty tracts are in the Northeastern industrial belt; they include Baltimore, Buffalo, Albany, and New Haven. The only metro area appearing on the Low-job-proximity/high-carlessness/2x Latino list is Youngstown, Ohio. This is principally because residents of 2X Latino tracts do not typically suffer from high rates of carlessness.

Moving down a row, the list of places in which residents of 2X African-American tracts suffer from both extremely poor hospital proximity and very high rates of carlessness includes five metros in the Southeast: Norfolk/Virginia Beach Memphis, Richmond, Charleston, and Winston-Salem. These metros are all in states where hospitals are few and far-between when measured on a per capita basis. Norfolk/Virginia Beach and Richmond also appear on the list of worst-case metros in which residents of 2X Poverty tracts suffer from poor hospital proximity and high carlessness rates, along with New York City-Newark, Chicago, Washington DC, San Francisco, St. Louis, Milwaukee, and New Orleans. These are all places in which poverty is spatially concentrated in neighborhoods far away from regional and local hospitals.

There are no metro areas in which the residents of 2X Latino tracts suffer from comparable hospital proximity and carlessness disadvantages.

Moving down another row, the list of places in which residents of 2X African-American tracts suffer both from reduced proximity to day care opportunities and very high rates of carlessness includes just two metros, New Orleans and Charleston. New Orleans also appears on the list of metros in which residents of 2X Poverty tracts suffer from poor day care proximity and high carlessness rates, along with Las Vegas, Milwaukee, El Paso, and Madison. These are all places in residents of 2X Black and 2X Poverty tracts suffer from higher-than-prevailing rates of carlessness and where local bus service is sporadic and infrequent.

Charleston, a worst-case standout, is the only metro area where residents of 2X African-American tracts suffer from extremely poor park proximity and extremely high rates of carlessness. Three other multiple offenders, Las Vegas, New Orleans, and El Paso, also appear on the list of metros in which the residents of 2X Poverty tracts are negatively impacted in terms of both park proximity and carlessness. Lancaster (Pennsylvania) is the sole metro area to appear on the 2X Latino/low-park-proximity/high carlessness list. All of these metros lack the type of high-quality/high-frequency bus service required to compensate for their high rates of carlessness and lack of neighborhood parks.

Rounding out the list of low-proximity-high-carlessness places, residents of 2X Black and 2X Poverty tracts in New Orleans also suffer from poor access to local libraries. They are joined on this dubious list by residents of 2X Black tracts in Charleston and 2X Poverty tracts in El Paso.

Table 7: Roster of Low-Proximity & Low-Mobility Metropolitan Areas for Different Combinations of Destination Activities and 2X Tracts Types

| Proximity & Mobility Combination ▼ | 2X African-American Tracts | 2X Latino Tracts | 2X Poverty Tracts |
|---|---|---|---|
| Low Proximity to Job Centers and High Carlessness Rates ► | New York-Newark NY-NJ<br>Chicago IL<br>Washington D.C.<br>Detroit MI<br>St. Louis MO<br>Pittsburgh PA<br>Cleveland OH<br>Richmond VA<br>Louisville KY<br>New Orleans LA | Youngstown OH | New York-Newark NY-NJ<br>Chicago IL<br>Washington D.C.<br>Baltimore MD<br>St. Louis MO<br>Virginia Beach VA<br>Louisville KY<br>Buffalo NY<br>Albany NY<br>New Haven CT |
| Low Proximity to Hospitals and High Carlessness Rates ► | Virginia Beach VA<br>Memphis TN<br>Richmond VA<br>Charleston SC<br>Winston NC | | New York-Newark NY<br>Chicago IL<br>Washington D.C.<br>San Francisco CA<br>St. Louis MO<br>Virginia Beach VA<br>Milwaukee WI<br>Richmond VA<br>New Orleans LA |
| Low Proximity to Day Care s and High Carlessness Rates ► | New Orleans LA<br>Charleston SC | | Las Vegas NV<br>Milwaukee WI<br>New Orleans LA<br>El Paso TX<br>Madison WI |
| Low Proximity to Parks and High Carlessness Rates ► | Charleston SC | Lancaster PA | Las Vegas NV<br>New Orleans LA<br>El Paso TX |
| Low Proximity to Libraries and High Carlessness Rates ► | New Orleans LA<br>Charleston SC | | New Orleans LA<br>El Paso TX |

# V. SUMMARY FINDINGS AND PLANNING PROPOSALS

It has become the conventional wisdom in recent years that residents of poor and minority urban neighborhoods suffer from systematic mobility and accessibility disadvantages when compared to their wealthier, Whiter, and more suburban counterparts, and that these disadvantages are contributing to broader economic equalities. Conceptually, this view traces its origins to the housing-jobs spatial mismatch hypothesis put forth by Harvard economist John Kain in 1968 to help explain Black workers' lower labor force participation and higher unemployment rates. It gained further currency in the early 2000s with research into the incidence of "healthy food deserts" which purported to connected higher rates of obesity among minorities and the urban poor to a lack of access to affordable and healthy food options.

That the poor suffer from reduced mobility when compared to moderate- and middle-income households is not at issue. This is principally because of the high fixed costs of owning a reliable automobile and the lack of frequent bus service in too many poor neighborhoods.

What is less clear is whether residents of poor and minority neighborhoods also suffer from systematic accessibility disparities across a fuller range of urban activities; and if such disparities are present, where and why are concentrated. This is an empirical question and one this paper tries to answer by comparing distance-based measures of proximity to metropolitan job centers and hospitals, and to local day care, park, and library facilities between all census tracts in a metropolitan area and those census tracts disproportionately occupied by minority and poor residents. The strength of this approach lies not in its complexity—our linear distance-based measures of proximity, for example, are generally not as accurate as similar non-linear network-based measures—but in its completeness. In addition to proximity to metropolitan job centers, we consider proximity to area hospitals, and to nearby day care centers, parks, and libraries. These various measures are constructed for all 107 U.S. metropolitan areas with a 2017 population of a half-million or more.

Our findings are striking. Subject to the limitations of our proximity-based measurement system, residents of minority and poverty neighborhoods live closer on average to area job centers, hospitals, day care facilities, and public parks and libraries than do residents of wealthier and Whiter neighborhoods. Averaged over the 107 U.S. metro areas with more than a half-million residents, residents of what we call 2X African-American census tracts, those in which the proportion of African-American residents is twice that of the metropolitan area, live 3 percent closer to major job centers, 6 percent closer to area hospitals, 35 percent closer to nearby day care facilities, 37 percent closer to the nearest public park, and 26 percent closer to the nearest public library. For residents of 2X Latino census tracts, the corresponding proximity advantages are 2 percent for jobs, 5 percent for hospitals, 27 percent for day care facilities, 31 percent for public parks, and 24 percent for the nearest public library. Residents of 2X poverty neighborhoods live closer still: 6 percent closer to jobs, 13 percent closer to jobs, 36 percent closer to nearby day care facilities, 39 percent closer to the nearest public parks, and 35 percent closer to the nearest library.

Given the low overall densities of most U.S. metropolitan areas and the resulting need for a car to meet every day travel needs, these proximity advantages are far less meaningful when potential travelers lack everyday access to an automobile; and it is in this realm, auto availability, that many 2X neighborhoods lag most. Among the 107 U.S. metro areas with more than a half-million population, residents of 2X African-American census tracts suffer from rates of carlessness that are 4 percent higher than the average rate of carlessness. Among 2X Latino neighborhoods, this differential is 2 percent higher, and among residents of 2X Poverty census tracts, it is a whopping 6.7% higher.

Some of the variation in 2X differentials can be explained by metro area size and location. Proximity differentials among 2X neighborhoods tend to be more favorable to local day care, park, and library facilities, and less favorable to job centers and hospitals among large metro areas than among mid-sized ones. Residents of 2X census tracts in Northeastern and Midwest metro areas live closer, on average, to jobs, hospitals, day care, parks, and libraries than do residents of 2X census tracts in metro areas in the South and West. The situation is the reverse for mobility. Rates of carlessness in 2X minority and poverty census tracts are higher than in other tracts among larger metro areas than among smaller ones; and also higher among Northeastern and Midwest metro areas than among those in the South and West.

Similarly, while proximity and carlessness differentials tend to be broadly comparable across the three types of 2X neighborhoods (i.e., if residents of 2X Black tracts live closer on average to local job centers, so too will the residents of 2X Latino and 2X Poverty tracts), there are a few notable differences. Residents of 2X Latino tracts, for example, generally have smaller proximity advantages to day care and parks than do residents of 2X Black tracts. Their mobility disadvantages, measured as the share of carless households, also tend to be smaller. By contrast, residents of 2X poverty neighborhoods suffer from greater mobility disadvantages than residents of 2X Black and 2X Latino tracts, while living closer to job opportunities, hospitals, and nearby parks.

These commonalities aside, there are still some significant differences among individual metropolitan areas. Table 8 summarizes these differences by comparing the number of metro areas in which 2X minority and poverty tracts have favorable versus unfavorable proximity and mobility ratings. A favorable rating is given to a metro area when the residents of its 2X tracts have superior proximity or mobility when compared to the full metropolitan area. An unfavorable rating is given when the residents of a metro area's 2X tracts have inferior or equal proximity, or a higher proportion of carlessness when compared to the metropolitan area. Among proximity types, the ratio of favorable-to-unfavorable ratings is on the order of 10-to-1 for day care facilities, parks, and libraries for all three 2X tract types. By contrast, across the full sample of metro areas, residents of 2X Poverty tracts have consistently better proximity to job centers and hospitals than do residents of 2X Latino and 2X Black tracts.

The situation is the opposite for mobility: There are only 8 metro areas in which residents of 2X Black tracts have lower rates of carlessness than do all metro area residents, versus 99 metro areas in which residents of 2X Black tracts suffer from higher rates of carlessness. For 2X Latino tracts, the ratio of unfavorable-to-favorable metro area ratings, at 25 versus 80 is only slightly better, while for 2X Poverty tracts, it is notably worse. Indeed, of the 107 US metro areas with more than a half-million population,

| Table 8: Counts of Metro Areas with Favorable and Unfavorable Proximity and Mobility Differentials for 2X Minority and Poverty Tracts | | | |
|---|---|---|---|
| Proximity & Mobility Measures ▼ | Counts of Metro Areas with Favorable and Unfavorable Proximity and Mobility Differential Rating | | |
| | 2X African-American Tracts | 2X Latino Tracts | 2X Poverty Tracts |
| Proximity to Job Centers | Favorable: 65<br>Unfavorable: 42 | Favorable: 69<br>Unfavorable: 36 | Favorable: 89<br>Unfavorable: 17 |
| Proximity to Hospitals | Favorable: 69<br>Unfavorable: 38 | Favorable: 61<br>Unfavorable: 46 | Favorable: 96<br>Unfavorable: 10 |
| Proximity to Day Care Facilities | Favorable: 96<br>Unfavorable: 11 | Favorable: 98<br>Unfavorable: 9 | Favorable: 98<br>Unfavorable: 9 |
| Proximity to Public Parks | Favorable: 97<br>Unfavorable: 10 | Favorable: 98<br>Unfavorable: 9 | Favorable: 98<br>Unfavorable: 9 |
| Proximity to Libraries | Favorable: 99<br>Unfavorable: 8 | Favorable: 96<br>Unfavorable:1 | Favorable: 103<br>Unfavorable: 4 |
| Carlessness Rates | Favorable: 9<br>Unfavorable: 98 | Favorable: 25<br>Unfavorable: 80 | Favorable: 3<br>Unfavorable: 104 |

there are only three in which the residents of 2X Poverty census tracts have lower rates of carlessness than the metro area as a whole.

These results are all subject to the caveat that not everyone who lives is a 2X African-American, Latino, or poverty census tract is Black, Latino, or poor; and that the attractiveness of a destination opportunity is a function of much more than proximity. Being located close to a job center is of little advantage if there are no jobs available, or if the skills prospective workers offer do not match the skills being sought by prospective employers. Similarly, living close to a hospital may be of little benefit if the hospital has a poor reputation, does not offer needed medical services, or is not a member of a patient's health care provider network. In terms of mobility, there are neighborhoods in some metro areas where residents can meet most of their daily travel needs by walking or using public transportation. For the most part, these neighborhoods are in older central cities in the Northeast.

In sum, for those interested in issues of metropolitan transportation access and mobility equity, the big challenges are mostly on the mobility side. In contrast to the conventional wisdom—and to our own initial expectations—residents of U.S. metropolitan areas living in poor and minority census tracts tend to live closer, not further away, from jobs, from hospitals, from local day care facilities, and from nearby parks and libraries. This is not to say that *all* African-Americans or Latinos or poor residents of urban areas have comparable access to these facilities as their wealthier or whiter neighbors, or access to facilities of comparable quality.

These findings—that a lack transportation accessibility among minority and poverty populations is not a systematic and pressing problem--should not be taken as an excuse for benignly neglecting those populations. Instead, it should be seen as an opportunity and jumping-off point for more carefully targeting metropolitan transportation planning efforts to meet the needs of those who are the most mobility-disadvantaged.

Since the 1962 establishment of metropolitan planning organizations (MPOs) as the federal government's preferred vehicle for funding urban transportation projects, transportation planners have prioritized projects on the basis of their anticipated time savings for all current and future travelers. This approach has favored auto users over transit riders, and projects that generate incremental-but-broadly-based benefits over projects that generate larger benefits for just a few. This widespread practice of focusing on improvements in systemwide accessibility rather than localized mobility is principally responsible for generating the deep mobility disparities faced by residents of minority and poverty neighborhoods in metropolitan areas across the country.

The results of this working paper suggest that the focus of metropolitan transportation planning efforts should shift away from promoting generalized accessibility and toward increasing mobility options for minority and poverty neighborhoods, especially those in large metropolitan areas in which there is a mobility mismatch between poverty neighborhoods, job centers, and the locations of key services.

This shift in thinking from emphasizing accessibility to focusing on ameliorating mobility disparities should not favor particular modes. It should help residents of poor and minority neighborhoods become car owners where private cars offer the greatest bump in personal and household mobility. Where ride-hailing services like Uber and Lyft most enhance personal mobility, public policy should favor their use. In neighborhoods where traditional public transit services can operate economically, service schedules, and in the case of buses, routes should be rejiggered to improve everyday mobility to essential destinations. Where people are inclined to walk, or use a bicycle or scooter, the use of those modes must be made easier. Last, local land use, urban design, and subdivision ordinances should be amended so that public and private developers working in poor and gentrifying neighborhoods must contribute to mobility-enhancing public improvements.

The good news is that this shift in emphasis is already underway in many cities and some MPOs. To go further, it will require additional financial resources. These resources cannot come from existing highway and transit budgets, most of which are vastly over-stretched. Instead, the U.S. Department of Transportation should require that each and every MPO establish a Mobility Planning office to assess which neighborhoods and population sub-groups are most lacking in multi-mobility options, and then work with private and public transportation service providers to fill those gaps. To move this process along, Congress should require the establishment of such offices as part of its next major transportation funding authorization bill as well as set aside implantation matching funds for MPOs the develop metropolitan-scale multi-modal mobility enhancement plans for the types of mobility-disadvantage communities and neighborhoods highlighted in this working paper.

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## Appendix A: African-American, Latino, and Poverty Population Shares of U.S. Metropolitan Areas with 500,000 and more Residents in 2017

| Metro Area (sorted alphabetically) | African-American Population Share | Latino Population Share | Poverty Population Share |
|---|---|---|---|
| Akron OH | 12.0% | 1.9% | 14.4% |
| Albany NY | 7.7% | 4.9% | 11.0% |
| Albuquerque NM | 2.6% | 48.5% | 18.6% |
| Allentown PA | 5.4% | 15.8% | 10.9% |
| Atlanta GA | 33.5% | 10.5% | 14.9% |
| Augusta GA | 35.6% | 5.2% | 19.0% |
| Austin TX | 7.3% | 32.2% | 13.3% |
| Bakersfield CA | 5.5% | 52.2% | 23.1% |
| Baltimore MD | 29.0% | 5.5% | 10.8% |
| Baton Rouge LA | 35.5% | 3.8% | 17.5% |
| Birmingham AL | 28.6% | 4.3% | 16.2% |
| Boise City ID | 0.9% | 13.3% | 14.7% |
| Boston MA | 8.0% | 10.6% | 10.2% |
| Bridgeport CT | 11.4% | 19.0% | 8.8% |
| Buffalo NY | 12.2% | 4.7% | 14.5% |
| Cape Coral FL | 8.6% | 20.2% | 15.5% |
| Charleston SC | 26.6% | 5.4% | 14.6% |
| Charlotte NC | 22.2% | 9.8% | 14.1% |
| Chattanooga TN | 13.7% | 4.3% | 15.2% |
| Chicago IL | 16.9% | 21.8% | 13.6% |
| Cincinnati OH | 12.2% | 3.0% | 13.8% |
| Cleveland OH | 20.0% | 5.5% | 15.2% |
| Colorado Springs CO | 6.0% | 16.1% | 11.2% |
| Columbia SC | 33.2% | 5.4% | 15.8% |
| Columbus OH | 14.8% | 3.9% | 14.4% |
| Dallas TX | 15.3% | 28.4% | 14.0% |
| Dayton OH | 15.5% | 2.6% | 16.4% |
| Deltona FL | 10.6% | 12.4% | 16.1% |
| Denver CO | 5.6% | 22.9% | 10.9% |
| Des Moines IA | 5.0% | 7.2% | 11.0% |
| Detroit MI | 22.4% | 4.3% | 16.2% |
| Durham NC | 26.8% | 11.4% | 16.2% |
| El Paso TX | 3.5% | 82.2% | 22.5% |
| Fayetteville AR | 2.3% | 15.8% | 15.3% |
| Fresno CA | 5.0% | 52.4% | 26.9% |
| Grand Rapids MI | 6.5% | 9.2% | 13.4% |
| Greensboro NC | 26.5% | 8.1% | 17.6% |
| Greenville SC | 16.7% | 6.6% | 15.8% |
| Harrisburg PA | 10.5% | 5.8% | 11.0% |
| Hartford CT | 11.0% | 14.2% | 10.4% |
| Honolulu HI | 2.4% | 9.6% | 9.5% |
| Houston TX | 17.2% | 36.7% | 15.3% |
| Indianapolis IN | 14.9% | 6.5% | 14.2% |
| Jackson MS | 49.1% | 2.3% | 19.7% |
| Jacksonville FL | 21.4% | 8.2% | 14.3% |
| Kansas City MO | 12.5% | 8.8% | 12.2% |
| Knoxville TN | 5.8% | 3.6% | 16.5% |
| Lakeland FL | 15.1% | 20.6% | 17.7% |
| Lancaster PA | 4.1% | 10.0% | 10.8% |
| Las Vegas NV | 11.0% | 30.7% | 15.0% |
| Lexington KY | 11.0% | 6.0% | 17.5% |
| Little Rock AR | 22.9% | 5.1% | 15.5% |
| Los Angeles CA | 6.7% | 45.0% | 16.5% |
| *(continued next column)* | | | |

| Metro Area (sorted alphabetically) | African-American Population Share | Latino Population Share | Poverty Population Share |
|---|---|---|---|
| Louisville KY | 14.1% | 4.5% | 14.1% |
| Madison WI | 4.4% | 5.7% | 12.0% |
| McAllen TX | 0.6% | 91.8% | 32.8% |
| Memphis TN | 46.6% | 5.3% | 19.4% |
| Miami FL | 21.4% | 44.2% | 16.7% |
| Milwaukee WI | 16.6% | 10.4% | 15.0% |
| Minneapolis MN | 7.8% | 5.7% | 9.8% |
| Modesto CA | 2.7% | 45.0% | 18.2% |
| Nashville TN | 15.2% | 7.0% | 13.5% |
| New Haven CT | 12.9% | 17.2% | 12.8% |
| New Orleans LA | 34.9% | 8.7% | 18.2% |
| New York-Newark NY-NJ | 17.1% | 24.1% | 14.2% |
| North Port FL | 6.6% | 12.1% | 12.6% |
| Ogden UT | 1.1% | 12.4% | 9.3% |
| Oklahoma City OK | 10.2% | 12.8% | 15.0% |
| Omaha NE | 7.7% | 10.1% | 11.8% |
| Orlando FL | 16.3% | 29.0% | 16.1% |
| Oxnard CA | 1.8% | 42.3% | 10.6% |
| Palm Bay FL | 10.2% | 9.7% | 14.0% |
| Philadelphia PA | 20.9% | 9.0% | 13.1% |
| Phoenix AZ | 5.2% | 30.5% | 16.5% |
| Pittsburgh PA | 8.2% | 1.6% | 12.0% |
| Portland ME | 1.9% | 1.8% | 10.4% |
| Portland OR | 2.8% | 11.6% | 12.8% |
| Providence RI | 5.6% | 12.1% | 13.4% |
| Provo UT | 0.6% | 11.2% | 12.6% |
| Raleigh NC | 20.1% | 10.4% | 11.6% |
| Richmond VA | 29.9% | 5.8% | 12.5% |
| Riverside CA | 7.4% | 50.0% | 17.7% |
| Rochester NY | 11.5% | 7.0% | 14.1% |
| Sacramento CA | 7.1% | 21.2% | 15.8% |
| Salt Lake City UT | 1.6% | 17.6% | 11.1% |
| San Antonio TX | 6.7% | 55.1% | 15.9% |
| San Diego CA | 5.0% | 33.4% | 14.0% |
| San Francisco CA | 7.6% | 21.9% | 10.7% |
| San Jose CA | 2.5% | 27.0% | 9.3% |
| Santa Rosa CA | 1.6% | 26.4% | 11.2% |
| Scranton–Wilkes Barre PA | 3.5% | 8.4% | 15.3% |
| Seattle WA | 5.6% | 9.7% | 10.9% |
| Spokane WA | 1.7% | 5.2% | 15.8% |
| Springfield MA | 7.1% | 19.2% | 17.0% |
| St. Louis MO | 18.3% | 2.9% | 12.7% |
| Stockton CA | 7.0% | 40.8% | 17.8% |
| Syracuse NY | 8.3% | 4.0% | 15.4% |
| Tampa FL | 12.0% | 18.4% | 15.1% |
| Toledo OH | 14.3% | 6.6% | 18.5% |
| Tucson AZ | 3.5% | 36.6% | 19.1% |
| Tulsa OK | 7.9% | 9.4% | 14.9% |
| Virginia Beach VA | 30.7% | 6.4% | 13.2% |
| Washington D.C. | 25.4% | 15.3% | 8.4% |
| Wichita KS | 7.6% | 12.6% | 14.2% |
| Winston NC | 17.7% | 10.0% | 18.0% |
| Worcester MA | 4.5% | 10.8% | 11.4% |
| Youngstown OH | 10.8% | 3.3% | 17.0% |

| Appendix B: Average Aerial Distances to Selected Activity Destinations by Metro Area | | | | | |
|---|---|---|---|---|---|
| Metropolitan Area (sorted alphabetically) | Average Kilometer Distance to all Large Job Centers | Average Kilometer Distance to Hospitals within 10 Miles | Average Kilometer Distance to Nearest Five Day Care Centers | Average Kilometer Distance to Nearest Public Park | Average Kilometer Distance to Nearest Library |
| Akron OH | 10.0 | 9.5 | 3.5 | 2.5 | 3.3 |
| Albany NY | 10.3 | 8.0 | 4.2 | 4.5 | 3.7 |
| Albuquerque NM | 10.2 | 9.7 | 3.3 | 4.0 | 3.7 |
| Allentown PA | 9.5 | 9.2 | 2.8 | 6.6 | 4.3 |
| Atlanta GA | 10.6 | 10.1 | 3.2 | 3.6 | 4.1 |
| Augusta GA | 9.8 | 9.2 | 5.2 | 10.6 | 5.6 |
| Austin TX | 10.1 | 9.8 | 2.6 | 3.3 | 4.2 |
| Bakersfield CA | 8.6 | 8.4 | 4.4 | 3.5 | 4.9 |
| Baltimore MD | 10.1 | 9.7 | 2.7 | 2.0 | 3.2 |
| Baton Rouge LA | 9.7 | 9.5 | 4.7 | 6.0 | 4.5 |
| Birmingham AL | 10.3 | 9.5 | 5.6 | 12.4 | 4.5 |
| Boise City ID | 9.5 | 8.0 | 10.4 | 3.9 | 4.2 |
| Boston MA | 9.9 | 9.2 | 3.1 | 2.4 | 2.3 |
| Bridgeport CT | 9.3 | 7.9 | 1.6 | 1.8 | 2.8 |
| Buffalo NY | 9.8 | 9.2 | 3.2 | 2.0 | 3.3 |
| Cape Coral FL | 10.8 | 9.7 | 4.7 | 3.5 | 5.6 |
| Charleston SC | 9.7 | 9.3 | 3.8 | 5.5 | 4.8 |
| Charlotte NC | 10.2 | 9.1 | 3.0 | 3.9 | 4.6 |
| Chattanooga TN | 9.0 | 9.9 | 6.2 | 4.3 | 6.5 |
| Chicago IL | 10.4 | 10.1 | 2.5 | 1.3 | 2.5 |
| Cincinnati OH | 10.2 | 10.0 | 4.0 | 3.2 | 3.7 |
| Cleveland OH | 10.2 | 9.9 | 3.0 | 2.2 | 2.7 |
| Colorado Springs CO | 9.9 | 9.6 | 3.6 | 2.5 | 4.6 |
| Columbia SC | 10.0 | 10.1 | 4.7 | 11.9 | 5.2 |
| Columbus OH | 10.1 | 9.3 | 3.9 | 2.5 | 3.7 |
| Dallas TX | 10.4 | 10.1 | 2.5 | 2.1 | 3.5 |
| Dayton OH | 10.0 | 9.7 | 3.7 | 1.9 | 3.3 |
| Deltona FL | 9.9 | 8.9 | 3.3 | 2.7 | 4.7 |
| Denver CO | 10.5 | 10.1 | 2.8 | 1.9 | 3.7 |
| Des Moines IA | 9.9 | 8.7 | 4.6 | 3.2 | 3.6 |
| Detroit MI | 10.5 | 10.1 | 4.5 | 2.4 | 3.4 |
| Durham NC | 10.6 | 7.7 | 2.6 | 3.6 | 4.0 |
| El Paso TX | 9.7 | 9.2 | 2.7 | 8.4 | 3.9 |
| Fayetteville AR | 10.8 | 8.9 | 5.6 | 9.0 | 6.2 |
| Fresno CA | 9.8 | 9.5 | 2.9 | 3.7 | 3.3 |
| Grand Rapids MI | 10.0 | 8.6 | 6.2 | 3.8 | 4.1 |
| Greensboro NC | 9.5 | 8.6 | 3.4 | 3.5 | 5.2 |
| Greenville SC | 10.1 | 9.1 | 4.7 | 5.6 | 5.2 |
| Harrisburg PA | 9.1 | 8.6 | 3.6 | 4.8 | 4.3 |
| Hartford CT | 10.2 | 9.3 | 2.0 | 2.6 | 2.8 |
| Honolulu HI | 9.2 | 9.1 | 2.2 | 1.3 | 2.5 |
| Houston TX | 10.3 | 10.0 | 2.6 | 3.1 | 4.1 |
| Indianapolis IN | 10.1 | 9.4 | 4.2 | 2.7 | 3.6 |
| Jackson MS | 10.3 | 9.7 | 4.0 | 7.4 | 4.0 |
| Jacksonville FL | 10.0 | 9.7 | 3.2 | 3.8 | 4.8 |
| Kansas City MO | 10.3 | 9.9 | 3.7 | 2.4 | 3.8 |
| Knoxville TN | 9.8 | 9.0 | 4.8 | 3.7 | 4.8 |
| Lakeland FL | 10.1 | 8.5 | 4.0 | 8.8 | 5.3 |
| Lancaster PA | 9.4 | 8.4 | 3.5 | 15.0 | 4.1 |
| Las Vegas NV | 10.7 | 10.1 | 3.5 | 2.7 | 3.7 |
| Lexington KY | 9.1 | 7.4 | 3.5 | 6.3 | 4.7 |
| Little Rock AR | 10.1 | 9.0 | 4.2 | 9.6 | 5.1 |
| Los Angeles CA | 10.3 | 10.2 | 1.5 | 1.2 | 2.1 |
| Louisville KY | 10.0 | 10.0 | 4.7 | 5.4 | 4.7 |
| Madison WI | 9.8 | 8.4 | 5.4 | 2.6 | 3.1 |
| McAllen TX | 9.1 | 9.3 | 2.3 | 6.2 | 4.5 |
| Memphis TN | 9.9 | 9.5 | 4.5 | 4.0 | 4.5 |
| Miami FL | 10.1 | 9.8 | 1.7 | 2.0 | 2.5 |
| Milwaukee WI | 9.9 | 10.0 | 3.9 | 1.5 | 3.2 |
| Minneapolis MN | 10.5 | 9.8 | 3.3 | 1.9 | 3.7 |
| Modesto CA | 7.6 | 7.3 | 2.3 | 1.4 | 4.0 |
| Nashville TN | 10.3 | 8.9 | 5.9 | 5.6 | 5.3 |
| New Haven CT | 10.2 | 7.4 | 1.7 | 1.9 | 2.7 |
| New Orleans LA | 9.3 | 8.8 | 6.9 | 2.5 | 2.6 |
| New York-Newark NY | 10.4 | 10.1 | 1.5 | 1.9 | 1.7 |
| North Port FL | 9.7 | 8.5 | 3.1 | 2.8 | 4.6 |
| Ogden UT | 9.9 | 9.4 | 4.1 | 2.0 | 4.0 |
| Oklahoma City OK | 10.1 | 9.4 | 2.5 | 2.6 | 4.0 |
| Omaha NE | 10.3 | 9.6 | 3.1 | 2.6 | 4.2 |
| Orlando FL | 10.3 | 9.8 | 2.9 | 3.7 | 4.1 |
| Oxnard CA | 9.6 | 8.8 | 3.7 | 2.4 | 5.0 |
| Palm Bay FL | 9.8 | 9.0 | 3.7 | 7.7 | 4.2 |
| Philadelphia PA | 10.3 | 10.0 | 2.0 | 2.3 | 2.9 |
| Phoenix AZ | 10.4 | 10.2 | 3.1 | 3.1 | 4.3 |
| Pittsburgh PA | 9.9 | 9.2 | 3.4 | 3.9 | 3.3 |
| Portland ME | 9.1 | 8.4 | 6.0 | 10.4 | 4.7 |
| Portland OR | 10.3 | 9.8 | 3.5 | 2.0 | 3.9 |
| Providence RI | 9.2 | 7.8 | 4.6 | 3.3 | 2.8 |
| Provo UT | 9.9 | 8.8 | 7.5 | 4.2 | 3.6 |
| Raleigh NC | 10.5 | 9.9 | 3.1 | 3.4 | 4.7 |
| Richmond VA | 10.3 | 10.1 | 3.8 | 5.9 | 4.2 |
| Riverside CA | 10.5 | 9.2 | 3.7 | 2.7 | 4.2 |
| Rochester NY | 9.8 | 9.3 | 4.7 | 3.5 | 3.3 |
| Sacramento CA | 9.8 | 9.5 | 2.5 | 2.3 | 3.7 |
| Salt Lake City UT | 10.1 | 9.6 | 3.5 | 2.2 | 2.9 |
| San Antonio TX | 10.4 | 9.9 | 3.4 | 4.1 | 4.6 |
| San Diego CA | 10.1 | 9.2 | 1.8 | 1.5 | 2.6 |
| San Francisco CA | 9.1 | 8.2 | 1.5 | 1.2 | 2.2 |
| San Jose CA | 10.0 | 9.7 | 1.4 | 1.1 | 2.3 |
| Santa Rosa CA | 9.9 | 8.1 | 3.9 | 2.4 | 4.5 |
| Scranton–Wilkes Barre PA | 9.0 | 8.1 | 3.7 | 7.0 | 4.0 |
| Seattle WA | 10.3 | 9.9 | 2.8 | 2.1 | 3.6 |
| Spokane WA | 9.2 | 8.2 | 2.8 | 2.5 | 3.8 |
| Springfield MA | 9.3 | 8.4 | 4.2 | 3.3 | 2.5 |
| St. Louis MO | 10.3 | 9.8 | 4.1 | 2.7 | 4.0 |
| Stockton CA | 7.9 | 7.2 | 1.8 | 1.8 | 3.5 |
| Syracuse NY | 9.4 | 7.8 | 4.8 | 2.9 | 3.5 |
| Tampa FL | 10.4 | 9.3 | 2.6 | 2.9 | 3.8 |
| Toledo OH | 9.7 | 9.3 | 4.6 | 3.9 | 3.5 |
| Tucson AZ | 10.2 | 9.9 | 3.6 | 2.7 | 4.2 |
| Tulsa OK | 10.1 | 9.4 | 4.4 | 4.9 | 4.4 |
| Virginia Beach VA | 9.9 | 9.6 | 2.9 | 3.0 | 3.7 |
| Washington D.C. | 10.3 | 9.9 | 2.2 | 2.0 | 3.4 |
| Wichita KS | 9.7 | 9.1 | 4.2 | 3.9 | 4.0 |
| Winston NC | 10.0 | 8.6 | 4.0 | 2.3 | 4.6 |
| Worcester MA | 9.0 | 7.5 | 6.1 | 3.0 | 2.7 |

*(continued next column)*

## Appendix C1: Proximity Differentials for 2X African-American Census Tracts by Destination Activity

| Metropolitan Area (sorted alphabetically) | Percentage Proximity Differential to all Large Job Centers | Percentage Proximity Differential to Hospitals within 10 Miles | Percentage Proximity Differential to Nearest Five Day Care Centers | Percentage Proximity Differential to Nearest Public Park | Percentage Proximity Differential to Nearest Library |
|---|---|---|---|---|---|
| Akron OH | -2% | -24% | -38% | -46% | -44% |
| Albany NY | -3% | -32% | -66% | -59% | -57% |
| Albuquerque NM | -3% | -8% | -48% | -70% | -28% |
| Allentown PA | -8% | -20% | -55% | -64% | -43% |
| Atlanta GA | 9% | 3% | -39% | -53% | -25% |
| Augusta GA | 2% | -6% | -56% | 21% | -32% |
| Austin TX | 3% | 7% | 6% | -14% | -11% |
| Bakersfield CA | -21% | -4% | 36% | 36% | -12% |
| Baltimore MD | 0% | -7% | -57% | -39% | -41% |
| Baton Rouge LA | -2% | -2% | -65% | -72% | -45% |
| Birmingham AL | 2% | 0% | -65% | -83% | -50% |
| Boise City ID | -5% | -4% | 14% | -58% | -17% |
| Boston MA | -3% | -5% | -42% | -56% | -34% |
| Bridgeport CT | -3% | -25% | -38% | -42% | -35% |
| Buffalo NY | -1% | -24% | -45% | -33% | -36% |
| Cape Coral FL | 2% | -13% | -26% | -6% | -11% |
| Charleston SC | -8% | -5% | 3% | 12% | -5% |
| Charlotte NC | -3% | 2% | -29% | -22% | -14% |
| Chattanooga TN | -15% | -10% | -64% | -60% | -32% |
| Chicago IL | 7% | -2% | -39% | -22% | -31% |
| Cincinnati OH | -1% | 0% | -46% | -60% | -46% |
| Cleveland OH | 3% | -3% | -43% | -33% | -36% |
| Colorado Springs CO | 2% | 5% | -19% | -43% | -26% |
| Columbia SC | -5% | -12% | -39% | -49% | -28% |
| Columbus OH | 1% | 7% | -44% | -48% | -31% |
| Dallas TX | 2% | 2% | -22% | -40% | -16% |
| Dayton OH | 5% | -14% | -23% | -43% | -5% |
| Deltona FL | -37% | -10% | -52% | -49% | -34% |
| Denver CO | -1% | 4% | -32% | -35% | -31% |
| Des Moines IA | -5% | -25% | -34% | -65% | -15% |
| Detroit MI | 3% | -4% | -51% | -44% | -27% |
| Durham NC | -5% | 5% | -46% | -67% | -43% |
| El Paso TX | 12% | 10% | -7% | 38% | 4% |
| Fayetteville AR | 11% | -9% | -22% | -69% | -23% |
| Fresno CA | 4% | 5% | -35% | -53% | -23% |
| Grand Rapids MI | -4% | -7% | -52% | -63% | -41% |
| Greensboro NC | -9% | -25% | -58% | -74% | -37% |
| Greenville SC | -4% | -10% | -38% | -50% | -28% |
| Harrisburg PA | -6% | -15% | -62% | -60% | -34% |
| Hartford CT | -10% | -13% | -27% | -53% | -41% |
| Honolulu HI | 11% | -1% | 14% | 50% | 25% |
| Houston TX | 5% | 5% | -34% | -30% | -20% |
| Indianapolis IN | 5% | 6% | -59% | -33% | -17% |
| Jackson MS | -2% | -20% | -67% | -69% | -40% |
| Jacksonville FL | -4% | 3% | -58% | -66% | -46% |
| Kansas City MO | 0% | -1% | -41% | -52% | -15% |
| Knoxville TN | -4% | -13% | -47% | -53% | -48% |
| Lakeland FL | -4% | -53% | -42% | -32% | -43% |
| Lancaster PA | -24% | -25% | -65% | 22% | -42% |
| Las Vegas NV | -6% | 3% | -8% | -31% | -1% |
| Lexington KY | 1% | 2% | -45% | -68% | -34% |
| Little Rock AR | -8% | 2% | -40% | -52% | -39% |
| Los Angeles CA | 3% | 5% | -21% | -2% | -12% |
| *(continued next column)* | | | | | |

| Metropolitan Area (sorted alphabetically) | Percentage Proximity Differential to all Large Job Centers | Percentage Proximity Differential to Hospitals within 10 Miles | Percentage Proximity Differential to Nearest Five Day Care Centers | Percentage Proximity Differential to Nearest Public Park | Percentage Proximity Differential to Nearest Library |
|---|---|---|---|---|---|
| Louisville KY | 2% | -10% | -73% | -76% | -50% |
| Madison WI | 1% | 22% | 7% | -67% | -19% |
| McAllen TX | -10% | -13% | 7% | -3% | -16% |
| Memphis TN | 1% | -2% | -56% | -71% | -39% |
| Miami FL | 1% | -1% | -34% | -12% | -20% |
| Milwaukee WI | -1% | 5% | 24% | -26% | -33% |
| Minneapolis MN | -4% | -7% | -47% | -54% | -40% |
| Modesto CA | -12% | -16% | -30% | -21% | 11% |
| Nashville TN | -4% | 0% | -41% | -60% | -40% |
| New Haven CT | -10% | -34% | -29% | -23% | -28% |
| New Orleans LA | 7% | 3% | 16% | -29% | -10% |
| New York-Newark NY | 2% | -1% | -55% | -28% | -39% |
| North Port FL | -14% | 0% | -39% | -20% | -22% |
| Ogden UT | -3% | -15% | -22% | -28% | -20% |
| Oklahoma City OK | -1% | 5% | -26% | -50% | -15% |
| Omaha NE | -3% | -1% | -49% | -67% | -40% |
| Orlando FL | -4% | 4% | -49% | -24% | -34% |
| Oxnard CA | -1% | 15% | 165% | 230% | 127% |
| Palm Bay FL | 3% | 3% | -34% | 65% | 1% |
| Philadelphia PA | -1% | -6% | -56% | -50% | -48% |
| Phoenix AZ | 2% | -3% | -8% | 3% | -11% |
| Pittsburgh PA | 2% | -1% | -54% | -44% | -55% |
| Portland ME | -17% | -22% | -62% | -83% | -18% |
| Portland OR | -1% | 4% | -36% | -51% | -24% |
| Providence RI | -11% | -25% | -41% | -64% | -45% |
| Provo UT | -6% | -12% | -30% | -44% | 10% |
| Raleigh NC | -1% | -14% | -34% | 31% | -29% |
| Richmond VA | 2% | -11% | -52% | -68% | -36% |
| Riverside CA | 1% | 4% | -2% | -1% | 21% |
| Rochester NY | -6% | -18% | -67% | -43% | -52% |
| Sacramento CA | 0% | 0% | -45% | -62% | -28% |
| Salt Lake City UT | -4% | 1% | -34% | -45% | -27% |
| San Antonio TX | 1% | 8% | -42% | -49% | -17% |
| San Diego CA | 5% | 8% | -27% | -28% | -28% |
| San Francisco CA | 4% | 2% | -17% | -17% | -20% |
| San Jose CA | 0% | 0% | -12% | -8% | -7% |
| Santa Rosa CA | -12% | 5% | -44% | -29% | -14% |
| Scranton–Wilkes PA | 3% | -32% | -54% | -49% | -95% |
| Seattle WA | -4% | -1% | -35% | -32% | -29% |
| Spokane WA | -3% | -13% | 20% | -22% | -21% |
| Springfield MA | -9% | 1% | -52% | -67% | -43% |
| St. Louis MO | 3% | -2% | -53% | -53% | -37% |
| Stockton CA | 2% | 11% | -20% | -26% | -21% |
| Syracuse NY | -16% | -40% | -63% | -73% | -64% |
| Tampa FL | -4% | -3% | -42% | -49% | -30% |
| Toledo OH | -6% | -6% | -54% | -68% | -45% |
| Tucson AZ | -3% | -1% | -37% | -41% | -16% |
| Tulsa OK | -3% | -2% | -60% | -75% | -36% |
| Virginia Beach VA | -2% | 0% | -40% | -50% | -40% |
| Washington D.C. | 4% | 7% | -26% | -33% | -17% |
| Wichita KS | -5% | -11% | -50% | -56% | -15% |
| Winston NC | -6% | 4% | -45% | -45% | -35% |
| Worcester MA | -18% | -32% | -56% | -68% | 10% |
| Youngstown OH | 8% | -17% | -41% | -43% | -31% |

## Appendix C2: Proximity Differentials for 2X Latino Census Tracts by Destination Activity

| Metropolitan Area (sorted alphabetically) | Percentage Proximity Differentials to all Large Job Centers | Percentage Proximity Differential to Hospitals within 10 Miles | Percentage Proximity Differential to Nearest Five Day Care Centers | Percentage Proximity Differential to Nearest Public Park | Percentage Proximity Differential to Nearest Library |
|---|---|---|---|---|---|
| Akron OH | -1% | -15% | -24% | -29% | -9% |
| Albany NY | 3% | -28% | -60% | -54% | -44% |
| Albuquerque NM | 18% | 7% | -38% | -99% | -12% |
| Allentown PA | -3% | -15% | -61% | -66% | -43% |
| Atlanta GA | -4% | -90% | -30% | -25% | -12% |
| Augusta GA | 21% | 11% | 20% | -25% | 6% |
| Austin TX | 1% | 9% | 40% | 66% | 7% |
| Bakersfield CA | -43% | 27% | -35% | -55% | -60% |
| Baltimore MD | -5% | -3% | -16% | -12% | -22% |
| Baton Rouge LA | -2% | 1% | -4% | -2% | -10% |
| Birmingham AL | -3% | -8% | 2% | 42% | -12% |
| Boise City ID | -37% | -32% | -58% | -30% | -17% |
| Boston MA | 0% | -9% | -47% | -59% | -33% |
| Bridgeport CT | -7% | -25% | -43% | -42% | -40% |
| Buffalo NY | -2% | -9% | -37% | -27% | -36% |
| Cape Coral FL | 9% | -14% | -16% | -8% | 11% |
| Charleston SC | 2% | 19% | -34% | -36% | -19% |
| Charlotte NC | 4% | 5% | -31% | -31% | -6% |
| Chattanooga TN | -10% | -12% | -58% | -57% | -44% |
| Chicago IL | -1% | 2% | -28% | -24% | -29% |
| Cincinnati OH | 0% | -5% | -32% | -50% | -27% |
| Cleveland OH | 0% | -4% | -20% | -33% | -32% |
| Colorado Springs CO | -1% | 6% | -36% | -66% | -35% |
| Columbia SC | 6% | 6% | 0% | -2% | -16% |
| Columbus OH | -1% | 8% | -44% | -44% | -32% |
| Dallas TX | 2% | 6% | -18% | -50% | -31% |
| Dayton OH | -1% | -2% | -20% | -19% | -5% |
| Deltona FL | 31% | 13% | -7% | -7% | 5% |
| Denver CO | -1% | 3% | -35% | -43% | -42% |
| Des Moines IA | -6% | -27% | -7% | -58% | -11% |
| Detroit MI | -8% | -8% | -17% | -30% | -19% |
| Durham NC | -7% | -10% | -33% | 87% | -22% |
| El Paso TX | 12% | 11% | -45% | -87% | -49% |
| Fayetteville AR | -3% | -18% | -56% | -34% | -43% |
| Fresno CA | | -1% | 176% | 209% | 52% |
| Grand Rapids MI | -4% | -16% | -58% | -75% | -48% |
| Greensboro NC | -11% | -6% | -34% | -43% | -26% |
| Greenville SC | -1% | 3% | -40% | -58% | -24% |
| Harrisburg PA | -10% | -15% | -57% | -55% | -41% |
| Hartford CT | -6% | -20% | -34% | -61% | -46% |
| Honolulu HI | 25% | 9% | 50% | 70% | 44% |
| Houston TX | 3% | 5% | -21% | -56% | -41% |
| Indianapolis IN | 0% | 3% | -46% | -33% | -19% |
| Jackson MS | -3% | 4% | -18% | -45% | -8% |
| Jacksonville FL | 4% | -3% | -44% | -36% | -22% |
| Kansas City MO | -3% | 8% | -41% | -59% | -21% |
| Knoxville TN | -7% | -16% | -20% | -30% | -26% |
| Lakeland FL | -8% | 25% | 45% | -18% | 21% |
| Lancaster PA | -31% | -28% | -72% | 30% | -54% |
| Las Vegas NV | -9% | -4% | -34% | -49% | -20% |
| Lexington KY | 5% | 1% | -20% | -30% | -17% |
| Little Rock AR | 6% | -1% | -30% | -25% | -20% |
| Los Angeles CA | 0% | 2% | -24% | -12% | -35% |

*(continued next column)*

| Metropolitan Area (sorted alphabetically) | Percentage Proximity Differentials to all Large Job Centers | Percentage Proximity Differential to Hospitals within 10 Miles | Percentage Proximity Differential to Nearest Five Day Care Centers | Percentage Proximity Differential to Nearest Public Park | Percentage Proximity Differential to Nearest Library |
|---|---|---|---|---|---|
| Louisville KY | -5% | 0% | -51% | -53% | -35% |
| Madison WI | -12% | 2% | 6% | -55% | 4% |
| McAllen TX | 5% | 9% | 18% | -5% | 20% |
| Memphis TN | 3% | 10% | -30% | -36% | -21% |
| Miami FL | 3% | 4% | -41% | -39% | -29% |
| Milwaukee WI | -12% | -7% | 13% | -33% | -29% |
| Minneapolis MN | -1% | -7% | -40% | -52% | -41% |
| Modesto CA | 3% | 9% | 14% | 19% | -50% |
| Nashville TN | -2% | -2% | -40% | -54% | -35% |
| New Haven CT | 5% | -44% | -28% | -45% | -21% |
| New Orleans LA | -3% | 2% | -33% | -32% | -25% |
| New York-Newark NY | 0% | -1% | -51% | -40% | -39% |
| North Port FL | -4% | -4% | -28% | -1% | -20% |
| Ogden UT | 1% | -6% | -38% | -50% | -19% |
| Oklahoma City OK | -2% | -2% | -37% | -63% | -34% |
| Omaha NE | -6% | 8% | -39% | -67% | -31% |
| Orlando FL | 4% | 0% | -13% | -16% | -3% |
| Oxnard CA | -2% | 11% | -37% | -53% | -57% |
| Palm Bay FL | 6% | 9% | -36% | 80% | -1% |
| Philadelphia PA | -2% | -6% | -30% | -37% | -33% |
| Phoenix AZ | 1% | 4% | -16% | -41% | -22% |
| Pittsburgh PA | -4% | -6% | -29% | -23% | -29% |
| Portland ME | -21% | -21% | -57% | -68% | -33% |
| Portland OR | 2% | -11% | -31% | -36% | -18% |
| Providence RI | -11% | -21% | -48% | -69% | -50% |
| Provo UT | -1% | 6% | -27% | -29% | -14% |
| Raleigh NC | 3% | -3% | 1% | -13% | -15% |
| Richmond VA | -1% | 11% | -40% | -53% | -22% |
| Riverside CA | -9% | -18% | -78% | -70% | -71% |
| Rochester NY | -5% | -18% | -76% | -54% | -48% |
| Sacramento CA | 0% | -16% | -44% | -65% | -28% |
| Salt Lake City UT | 2% | 11% | -20% | -47% | -17% |
| San Antonio TX | | -5% | 131% | 183% | 11% |
| San Diego CA | -5% | -9% | -38% | -38% | -32% |
| San Francisco CA | 1% | 0% | -18% | -12% | -23% |
| San Jose CA | -3% | -6% | -3% | -5% | -32% |
| Santa Rosa CA | 1% | -5% | -66% | -4% | -46% |
| Scranton–Wilkes PA | -13% | -38% | -59% | -16% | -39% |
| Seattle WA | -3% | -1% | -25% | -32% | -21% |
| Spokane WA | -20% | -15% | 52% | -28% | -17% |
| Springfield MA | -9% | -9% | -61% | -66% | -37% |
| St. Louis MO | -1% | -4% | -31% | -28% | -22% |
| Stockton CA | 60% | -2% | -10% | -19% | -28% |
| Syracuse NY | -12% | -34% | -52% | -58% | -39% |
| Tampa FL | -1% | 1% | -16% | -8% | -5% |
| Toledo OH | -3% | -3% | -21% | -60% | -41% |
| Tucson AZ | -3% | 2% | -30% | -39% | -34% |
| Tulsa OK | -1% | 16% | -55% | -72% | -29% |
| Virginia Beach VA | 5% | 3% | -22% | -19% | 5% |
| Washington D.C. | -1% | -5% | -35% | -51% | -30% |
| Wichita KS | -10% | -1% | -45% | -62% | -30% |
| Winston NC | 1% | 11% | -38% | -21% | -31% |
| Worcester MA | -17% | -43% | -27% | -59% | -22% |
| Youngstown OH | 18% | 3% | -41% | -40% | -40% |

## Appendix C3: Proximity Differentials for 2X Poverty Census Tracts by Destination Activity

| Metropolitan Area (sorted alphabetically) | Percentage Proximity Differetial to all Large Job Centers | Percentage Proximity Differential to Hospitals within 10 Miles | Percentage Proximity Differential to Nearest Five Day Care Centers | Percentage Proximity Differential to Nearest Public Park | Percentage Proximity Differential to Nearest Library | Metropolitan Area (sorted alphabetically) | Percentage Proximity Differetial to all Large Job Centers | Percentage Proximity Differential to Hospitals within 10 Miles | Percentage Proximity Differential to Nearest Five Day Care Centers | Percentage Proximity Differential to Nearest Public Park | Percentage Proximity Differential to Nearest Library |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Akron OH | -5% | -21% | -40% | -42% | -42% | Louisville KY | 2% | -14% | -62% | -78% | -46% |
| Albany NY | 0% | -32% | -70% | -78% | -63% | Madison WI | -9% | -41% | 37% | -51% | -45% |
| Albuquerque NM | -13% | -23% | 54% | 70% | 10% | McAllen TX | | | 335% | 239% | 341% |
| Allentown PA | -8% | -20% | -60% | -66% | -55% | Memphis TN | 1% | -4% | -48% | -53% | -38% |
| Atlanta GA | -2% | -3% | -46% | -44% | -42% | Miami FL | -3% | -9% | -39% | -16% | -22% |
| Augusta GA | -17% | -27% | -45% | 12% | -41% | Milwaukee WI | -9% | 0% | 32% | -28% | -40% |
| Austin TX | -36% | -19% | 54% | 20% | 22% | Minneapolis MN | -7% | -16% | -51% | -35% | -46% |
| Bakersfield CA | -19% | -24% | -66% | -62% | -55% | Modesto CA | 13% | 27% | -25% | -42% | -22% |
| Baltimore MD | -1% | -12% | -57% | -42% | -51% | Nashville TN | -11% | -15% | -40% | -50% | -49% |
| Baton Rouge LA | -5% | 0% | -65% | -82% | -40% | New Haven CT | -1% | -54% | -33% | -46% | -39% |
| Birmingham AL | -2% | -6% | -66% | -79% | -55% | New Orleans LA | -3% | -3% | 35% | 1% | -3% |
| Boise City ID | -26% | -46% | -33% | -66% | -62% | New York-Newark NY | -1% | -3% | -63% | -40% | -45% |
| Boston MA | -8% | -18% | -52% | -57% | -42% | North Port FL | -13% | -20% | -58% | -25% | -35% |
| Bridgeport CT | -3% | -25% | -42% | -45% | -50% | Ogden UT | -6% | -14% | -39% | -49% | -24% |
| Buffalo NY | -2% | -19% | -51% | -46% | -34% | Oklahoma City OK | -7% | -5% | -43% | -67% | -38% |
| Cape Coral FL | -13% | -7% | -41% | -37% | -22% | Omaha NE | -12% | 1% | -53% | -70% | -40% |
| Charleston SC | -17% | -7% | -49% | -62% | -55% | Orlando FL | -5% | -4% | -41% | -31% | -30% |
| Charlotte NC | -8% | -12% | -36% | -42% | -33% | Oxnard CA | 5% | 8% | -34% | -41% | -49% |
| Chattanooga TN | -21% | -11% | -63% | -67% | -47% | Palm Bay FL | -16% | -13% | -65% | -9% | -39% |
| Chicago IL | 4% | -2% | -43% | -25% | -37% | Philadelphia PA | -8% | -9% | -59% | -51% | -52% |
| Cincinnati OH | -7% | -11% | -36% | -59% | -42% | Phoenix AZ | 0% | 1% | 1% | -32% | -17% |
| Cleveland OH | -1% | -6% | -42% | -36% | -45% | Pittsburgh PA | -6% | -14% | -44% | -29% | -56% |
| Colorado Springs CO | -5% | -5% | -50% | -72% | -43% | Portland ME | -23% | -39% | -41% | -50% | -41% |
| Columbia SC | -10% | -10% | -35% | -44% | -39% | Portland OR | 0% | -5% | -40% | -51% | -37% |
| Columbus OH | 1% | -6% | -51% | -54% | -42% | Providence RI | -13% | -39% | -45% | -60% | -54% |
| Dallas TX | -1% | -2% | -10% | -6% | -22% | Provo UT | -2% | -14% | -55% | -67% | -30% |
| Dayton OH | -1% | -23% | -39% | -48% | -21% | Raleigh NC | 0% | -12% | -16% | 27% | -36% |
| Deltona FL | -42% | -9% | -64% | -67% | -55% | Richmond VA | -2% | -6% | -49% | -66% | -46% |
| Denver CO | -4% | 0% | -40% | -45% | -46% | Riverside CA | 4% | -10% | -12% | -15% | -35% |
| Des Moines IA | -6% | -35% | -37% | -56% | -19% | Rochester NY | -6% | -22% | -59% | -45% | -48% |
| Detroit MI | -1% | -4% | -48% | -45% | -33% | Sacramento CA | -4% | -10% | -45% | -61% | -28% |
| Durham NC | -2% | -29% | -41% | -29% | -39% | Salt Lake City UT | -5% | 0% | -41% | -45% | -35% |
| El Paso TX | -13% | -21% | 43% | 41% | 11% | San Antonio TX | 1% | 1% | -55% | -70% | -51% |
| Fayetteville AR | 16% | -23% | -64% | -62% | -56% | San Diego CA | -2% | -4% | -48% | -35% | -43% |
| Fresno CA | 4% | 4% | -57% | -68% | -32% | San Francisco CA | -2% | -3% | -36% | -25% | -34% |
| Grand Rapids MI | -4% | -35% | -44% | -62% | -49% | San Jose CA | -7% | 1% | -9% | -10% | -30% |
| Greensboro NC | -14% | -39% | -56% | -74% | -47% | Santa Rosa CA | -2% | -4% | 8% | 14% | -50% |
| Greenville SC | -3% | -2% | -40% | -63% | -27% | Scranton–Wilkes PA | -2% | -44% | -66% | -37% | -61% |
| Harrisburg PA | -13% | -22% | -42% | -35% | -54% | Seattle WA | -9% | -11% | -40% | -42% | -44% |
| Hartford CT | -7% | -24% | -37% | -32% | -47% | Spokane WA | -25% | -16% | -2% | -49% | -44% |
| Honolulu HI | -19% | -16% | -20% | -12% | -15% | Springfield MA | -8% | -11% | -62% | -68% | -52% |
| Houston TX | 2% | 5% | -31% | -44% | -38% | St. Louis MO | 0% | -5% | -48% | -41% | -39% |
| Indianapolis IN | -2% | -6% | -48% | -45% | -31% | Stockton CA | 24% | -8% | -21% | -39% | -32% |
| Jackson MS | -3% | -16% | -53% | -54% | -43% | Syracuse NY | -18% | -52% | -66% | -72% | -64% |
| Jacksonville FL | -10% | -8% | -61% | -65% | -49% | Tampa FL | -7% | -4% | -36% | -34% | -19% |
| Kansas City MO | -3% | -2% | -35% | -47% | -23% | Toledo OH | -9% | -13% | -55% | -23% | -47% |
| Knoxville TN | -9% | -33% | -64% | -74% | -51% | Tucson AZ | -4% | -4% | -41% | -40% | -40% |
| Lakeland FL | -3% | -35% | -37% | -9% | -36% | Tulsa OK | -2% | 0% | -55% | -74% | -39% |
| Lancaster PA | -23% | -28% | -69% | 22% | -53% | Virginia Beach VA | -1% | -2% | -39% | -46% | -40% |
| Las Vegas NV | -10% | -8% | -9% | -17% | -23% | Washington D.C. | -1% | 0% | -45% | -38% | -42% |
| Lexington KY | -8% | -30% | -64% | -67% | -55% | Wichita KS | -11% | -5% | -49% | -67% | -34% |
| Little Rock AR | -12% | 1% | -54% | -40% | -40% | Winston NC | -1% | -2% | -49% | -53% | -45% |
| Los Angeles CA | 1% | -2% | -25% | -1% | -26% | Worcester MA | -23% | -42% | -43% | -70% | -22% |
| *(continued next column)* | | | | | | Youngstown OH | 6% | -15% | -31% | -27% | -36% |

## Appendix D: Carlessness Differentials for 2X African-American, Latino, and Poverty Census Tracts by Metropolitan Area

| Metro Area (sorted alphabetically) | 2X African-American Census Tracts | 2X Latino Census Tracts | 2X Poverty Census Tracts | Metro Area (sorted alphabetically) | 2X African-American Census Tracts | 2X Latino Census Tracts | 2X Poverty Census Tracts |
|---|---|---|---|---|---|---|---|
| Akron OH | 4.8% | 1.1% | 5.6% | Louisville KY | 9.5% | 0.5% | 9.8% |
| Albany NY | 11.2% | 9.2% | 11.5% | Madison WI | -1.8% | 1.3% | 17.7% |
| Albuquerque NM | 2.0% | / | 5.1% | McAllen TX | 0.0% | 0.0% | 0.0% |
| Allentown PA | 7.5% | 8.9% | 9.7% | Memphis TN | 6.5% | -1.4% | 7.7% |
| Atlanta GA | 4.7% | 2.4% | 8.0% | Miami FL | 2.8% | 0.1% | 6.9% |
| Augusta GA | 4.3% | -1.7% | 7.5% | Milwaukee WI | -4.1% | 0.9% | 9.1% |
| Austin TX | 0.1% | 0.1% | -0.1% | Minneapolis MN | 5.1% | 3.2% | 7.3% |
| Bakersfield CA | 1.2% | 1.7% | 6.0% | Modesto CA | -0.3% | / | 1.1% |
| Baltimore MD | 11.6% | -4.2% | 15.6% | Nashville TN | 2.7% | 0.5% | 3.9% |
| Baton Rouge LA | 2.8% | -0.2% | 3.9% | New Haven CT | 7.9% | 2.0% | 10.5% |
| Birmingham AL | 3.0% | -0.5% | 4.8% | New Orleans LA | 7.6% | -1.3% | 14.2% |
| Boise City ID | -0.1% | -0.3% | 1.9% | New York-Newark NY-NJ | 11.1% | 18.4% | 26.8% |
| Boston MA | 7.2% | 7.4% | 13.7% | North Port FL | 1.4% | 1.1% | 2.4% |
| Bridgeport CT | 6.0% | 7.6% | 8.9% | Ogden UT | 0.0% | 0.0% | 0.0% |
| Buffalo NY | 11.1% | 6.2% | 11.0% | Oklahoma City OK | 1.9% | 0.3% | 2.4% |
| Cape Coral FL | 0.3% | 1.2% | 4.2% | Omaha NE | 4.2% | 1.8% | 5.2% |
| Charleston SC | 5.9% | 0.8% | 7.2% | Orlando FL | 4.5% | -0.1% | 6.9% |
| Charlotte NC | 3.0% | 1.7% | 5.2% | Oxnard CA | -0.3% | 1.0% | 1.6% |
| Chattanooga TN | 5.6% | -0.5% | 6.2% | Palm Bay FL | 4.4% | -0.6% | 6.6% |
| Chicago IL | 7.6% | -0.6% | 10.2% | Philadelphia PA | 12.5% | 10.3% | 16.5% |
| Cincinnati OH | 6.8% | 3.0% | 8.5% | Phoenix AZ | 2.0% | 2.5% | 4.8% |
| Cleveland OH | 6.1% | 2.0% | 8.7% | Pittsburgh PA | 9.8% | 4.4% | 11.8% |
| Colorado Springs CO | 1.2% | 2.3% | 2.5% | Portland ME | 6.0% | 4.0% | 7.8% |
| Columbia SC | 4.7% | 0.1% | 6.2% | Portland OR | 3.6% | 0.5% | 7.1% |
| Columbus OH | 4.6% | 1.7% | 5.7% | Providence RI | 4.0% | 5.1% | 7.4% |
| Dallas TX | 1.9% | 0.9% | 4.9% | Provo UT | 0.0% | 0.0% | 0.0% |
| Dayton OH | 5.4% | 3.5% | 6.8% | Raleigh NC | 5.0% | 0.6% | 4.6% |
| Deltona FL | 4.6% | -1.2% | 6.8% | Richmond VA | 8.5% | -1.4% | 9.1% |
| Denver CO | 2.0% | 0.5% | 3.2% | Riverside CA | 0.6% | 0.0% | 2.8% |
| Des Moines IA | 1.5% | 1.5% | 2.5% | Rochester NY | 9.9% | 8.8% | 11.2% |
| Detroit MI | 7.1% | 0.2% | 8.5% | Sacramento CA | 2.0% | 1.1% | 3.9% |
| Durham NC | 5.3% | 2.7% | 4.6% | Salt Lake City UT | 0.0% | 0.0% | 0.0% |
| El Paso TX | 0.0% | 1.4% | 13.6% | San Antonio TX | 0.9% | -3.0% | 4.8% |
| Fayetteville AR | 1.3% | 0.7% | 2.2% | San Diego CA | 1.0% | 1.3% | 3.4% |
| Fresno CA | 2.9% | -1.9% | 5.9% | San Francisco CA | 0.3% | -1.7% | 10.3% |
| Grand Rapids MI | 1.9% | 3.4% | 4.0% | San Jose CA | 0.9% | 0.2% | 2.2% |
| Greensboro NC | 2.7% | 1.8% | 4.6% | Santa Rosa CA | 0.0% | 0.5% | 2.0% |
| Greenville SC | 4.5% | 1.4% | 5.0% | Scranton–Wilkes Barre PA | 3.8% | 3.6% | 6.2% |
| Harrisburg PA | 7.4% | 15.2% | 9.8% | Seattle WA | 1.9% | 0.7% | 6.7% |
| Hartford CT | 8.3% | 9.3% | 10.8% | Spokane WA | 1.0% | 0.5% | 5.9% |
| Honolulu HI | -0.3% | -2.9% | 7.9% | Springfield MA | 3.2% | 8.6% | 7.0% |
| Houston TX | -0.1% | -0.1% | 0.0% | St. Louis MO | 8.1% | 0.8% | 9.8% |
| Indianapolis IN | 2.7% | 2.3% | 4.1% | Stockton CA | 2.9% | 0.4% | 3.6% |
| Jackson MS | 0.9% | -0.5% | 2.9% | Syracuse NY | 13.2% | 12.7% | 14.4% |
| Jacksonville FL | 6.5% | 1.6% | 7.7% | Tampa FL | 4.1% | 1.7% | 5.4% |
| Kansas City MO | 4.5% | 1.3% | 5.0% | Toledo OH | 6.5% | 3.0% | 7.8% |
| Knoxville TN | 2.9% | 1.9% | 6.6% | Tucson AZ | 3.1% | 0.8% | 5.2% |
| Lakeland FL | 4.2% | 1.4% | 4.8% | Tulsa OK | 3.9% | 1.1% | 3.9% |
| Lancaster PA | 3.3% | 4.9% | 5.8% | Virginia Beach VA | 7.0% | -0.8% | 8.8% |
| Las Vegas NV | 3.4% | 1.9% | 9.4% | Washington D.C. | 5.9% | -0.1% | 12.3% |
| Lexington KY | 2.9% | 3.0% | 6.2% | Wichita KS | 3.0% | 1.2% | 3.3% |
| Little Rock AR | 3.5% | 0.4% | 7.2% | Winston NC | 5.7% | 2.3% | 8.6% |
| Los Angeles CA | 1.6% | 2.5% | 8.4% | Worcester MA | 4.1% | 6.3% | 8.0% |
| *(continued next column)* | | | | Youngstown OH | 2.7% | 4.5% | 3.6% |

## Appendix E: 2X Census Tract Carlessness Rate Correlation Coefficients by Region, and to Population Characteristics, Income and Poverty Measures, and Metropolitan Spatial Structure

| Metro Area Characteristic | | Correlation Coefficients for 2017 Carlessness Rates by Census Tract Grouping | | | |
|---|---|---|---|---|---|
| | | All Tracts | 2x African-American Tracts | 2x Latino Tracts | 2x Poverty Tracts |
| Carlessness Rates | 2017 Carlesness Rate: All Tracts | 1.00* | | | |
| | 2017 Carlesness Rate: 2x African-American Tracts | 0.86* | 1.00* | | |
| | 2017 Carlesness Rate: 2x Latino Tracts | 0.85* | 0.79* | 1.00* | |
| | 2017 Carlesness Rate: 2x Poverty Tracts | 0.94* | 0.88* | 0.80* | 1.00* |
| Population Measures | Metro Area Population, 2017 | 0.57* | 0.38* | 0.43* | 0.50* |
| | Metro population > 2 million (0/1) | 0.21 | 0.16 | 0.08 | 0.20 |
| | Metro population: 1 - 2 million (0/1) | 0.01 | 0.08 | -0.03 | 0.03 |
| | Metro population: 0.5 - 1 million (0/1) | -0.21 | -0.22 | -0.05 | -0.21 |
| | Percent Population Change, 2000-2017 | -0.40* | -0.41* | -0.32* | -0.40* |
| Race and Demographic Measures | African-American Population Share, 2016 | 0.17 | 0.27* | -0.03 | 0.20 |
| | Latino Population Share, 2016 | -0.18 | -0.36* | -0.17 | 0.20 |
| | Black-White Dissimilarity Index, 2016 | 0.49* | 0.53* | 0.43* | 0.47* |
| | Latino/Non-Latino Dissimilarity Index, 2016 | 0.26* | 0.12 | 0.37* | 0.19 |
| | Population Median Age, 2016 | 0.30* | 0.40* | 0.33* | 0.35* |
| | Share of Foreign-born Residents, 2016 | 0.08 | -0.12 | 0.23 | 0.01 |
| Income Measures | Median Household Income, 2017 | 0.17 | 0.11 | 0.17 | 0.17 |
| | Poverty Rate, 2017 | -0.05 | -0.08 | -0.11 | -0.05 |
| | Poverty Rate Moran's I, 2000 | 0.28* | 0.40* | 0.32* | 0.33* |
| | 95-20% Income Ratio,2012 | 0.44* | 0.31* | 0.31* | 0.38* |
| Regional Fixed Effect Measures | Northeast Region (0/1) | 0.53* | 0.61* | 0.69* | 0.55* |
| | Midwest Region (0/1) | 0.06 | -0.02 | -0.01 | 0.02 |
| | Southeast Region (0/1) | -0.28* | -0.17 | -0.39* | 0.23 |
| | Western Region (0/1) | -0.23 | -0.37* | -0.22 | -0.29* |
| Spatial Structure Measures | NLCD-based Population Density 2010 | 0.42* | 0.21 | 0.37* | 0.38* |
| | Core Area Population Share, 2010 | 0.27* | 0.22 | 0.35* | 0.26 |
| | Core Area Population Growth Rate, 2000-2010 | -0.23 | -0.30* | 0.14 | -0.25 |
| | Density Gradient Intercept Value, 2010 | 0.36* | 0.22 | 0.25 | 0.34* |
| | Density Gradient Slope Coefficient Value, 2010 | 0.00 | 0.02 | 0.05 | 0.01 |
| | Employment Moran's I, 2013 | 0.12 | 0.13 | 0.13 | 0.10 |

* indicates statistical significance at the .01 level

[1] As a practical matter, accessibility involves jointly maximizing the number of travel destination activities and opportunities of interest, the speed at which those activities can be accessed, and some sort of decay function that favors closer activities over more distant ones (Duranton and Guerra, 2016). Historically, accessibility's speed component was calculated using the uncongested travel speed of the dominant travel mode, which in the U.S. more often than not, was the private car. More recently, as congestion has become more severe and commonplace, and as the differential extent of carlessness has become better understood, analysts have taken to measuring accessibility via different modes.

Measurements of mobility, likewise, may give more or less emphasis to particular factors depending on the context. In the U.S., where auto travel is dominant, the operationalization of mobility emphasizes travel speed as the primary measure of trip-making convenience. In the U.K., by contrast, mobility is typically operationalized as expected travel time relative to the time normally budgeted for similar trips regardless of mode.

[2] Readers unfamiliar with the ACS commonly confuse it with the Decennial Census. Both are based on household survey data, but whereas the Decennial Census is a true census that surveys all residents, the ACS is a sample survey that reaches roughly 2.4 percent of U.S. households. As with any sample survey, this means that its results include some amount of sampling error. Fortunately, all ACS estimates are accompanied by calculations of margins-of-error, making it possible to reliably compare ACS estimates across time and space.

[3] This discounting of more distant opportunities is generally done using a non-linear distance-decay function in which the influence of successively further opportunities is reduced by more than their linear distance.

[4] Access to hospitals and health care is especially important for low-income patients, which research suggests having adverse health outcomes at a far greater rate than middle-income or wealthier patients (Kreiger, et.al. 2005). A more complete picture of health care access disparities in presented in periodic monographs published by Harvard University's T.C. Chan Center Public Health Disparities Geocoding Project.

[5] Different parks do indeed provide different types and levels of services, but the database we are using emphasizes comprehensiveness over detail and lacks information on the mix of services and facilities available at each park.

[6] For more detail on the derivation of these metrics, refer to Landis (2017).

[7] In the six metro areas in which doubling the proportion of Latinos exceeded 100%, we used a 95% threshold to identify 2X Latino tracts.

[8] Just as we did for proximity in Table 3, we analyzed rates of carlessness as a function of population size, local demographic and socio-economic characteristics, and measures of urban spatial structure. These comparisons are presented as correlation coefficients in Appendix E. Among the factors most consistently and strongly associated with higher rates of carlessness are the size of the metro area, the level of Black-White segregation, population density, income inequality, and the degree to which poverty is spatially concentrated.