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Redefining Neighborhoods Using Common Destinations: Social Characteristics of Activity Spaces and Home Census Tracts Compared

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Abstract

Research on neighborhood effects has focused largely on residential neighborhoods, but people are exposed to many other places in the course of their daily lives—at school, at work, when shopping, and so on. Thus, studies of residential neighborhoods consider only a subset of the social-spatial environment affecting individuals. In this article, we examine the characteristics of adults' "activity spaces"—spaces defined by locations that individuals visit regularly, in Los Angeles County, California. Using geographic information system (GIS) methods, we define activity spaces in two ways and estimate their socioeconomic characteristics. Our research has two goals. First, we determine whether residential neighborhoods represent the social conditions to which adults are exposed in the course of their regular activities. Second, we evaluate whether particular groups are exposed to a broader or narrower range of social contexts in the course of their daily activities. We find that activity spaces are substantially more heterogeneous in terms of key social characteristics, compared to residential neighborhoods. However, the characteristics of both home neighborhoods and activity spaces are closely associated with individual characteristics. Our results suggest that most people experience substantial segregation across the range of spaces in their daily lives, not just at home.

Keywords

Neighborhood; Activity spaces; Isolation; Segregation; GIS methods

Introduction

Throughout our lives, we shape and are shaped by the social and physical environments surrounding us. A growing literature has examined the importance of place-based environments for issues as diverse as child development, labor market outcomes, health, and political behavior (Braveman et al. 2010; Cho et al. 2006; Covington 2009; Entwisle 2007;

Fauth et al. 2007; Sampson 2012; Sastry and Pebley 2010). This literature generally focuses on the places where people live, but adults and children are exposed to a range of other places in the course of their daily lives—for example, their school, their workplace(s), and stores and shopping centers. Thus, studies focused on residential neighborhoods consider only a subset of the potentially relevant contextual influences on individuals.

In this article, we examine one approach to this problem using a sample of the routine destinations of adults in Los Angeles County, California. We employ unusual data from the 2000–2001 Los Angeles Family and Neighborhood Survey–Wave 1 (L.A.FANS), which include specific locations of adult respondents' homes, grocery stores, workplaces, health care facilities, and places of worship—a set of places where they regularly spend time. Using these data and GIS methods, we define activity spaces in two different ways and estimate their socioeconomic characteristics based on 2000 U.S. census data. Activity spaces include but often extend well beyond residential neighborhoods.

Our study has two distinct goals. First, we compare the characteristics of individuals' activity spaces with those of their residential neighborhoods. Our goal is to determine whether residential neighborhoods adequately represent the social conditions (e.g., poverty, ethnic composition) to which adults are exposed in the course of their regular activities. If activity spaces and residential neighborhoods differ substantially, then studies on residential neighborhood effects may be missing an important part of the picture, as some have suggested (Crowder and South 2011; Inagami et al. 2007; Kwan 2012; Matthews 2011; Sastry et al. 2002). Activity spaces may better reflect the context that individuals experience because they capture the spatial range of daily experience.

Our second goal is to compare the characteristics of activity spaces among individuals of different social classes, races/ethnicities, and immigrant statuses. Our objective is to assess the degree to which people encounter groups *other than their own*, as part of their routine activities. Racial/ethnic and income segregation are important, in part, because contact among social groups may have important effects on a person's assumptions about, and attitudes toward, other social groups and how they live (Chaskin and Joseph 2011; DiPrete et al. 2011; Ellison et al. 2011; Pettigrew 2008; Rocha and Espino 2010). These assumptions and attitudes may be important for social solidarity, political behavior, and many other aspects of urban life. In this article, we examine the degree of isolation across social groups in Los Angeles by investigating the social characteristics of individuals' activity spaces as a function of individuals' attributes.

Background

Since the 1970s, metropolitan areas of the United States have experienced both increasing income inequality and growing spatial segregation by family income (Reardon and Bischoff 2011). The affluent are more likely to be isolated from other groups than are the poor. Latino-white and Asian-white segregation increased between 1990 and 2010; and although African American white segregation has declined since 1990, African Americans remain the most segregated racial/ethnic group in the United States (Frey 2012).

Neighborhood Effects: Residential Versus Activity Space

Growing income segregation in metropolitan areas heightens the importance of research on the social consequences of concentrated poor and affluent neighborhoods. Since the 1990s, many observational and experimental studies have found associations between residential neighborhood socioeconomic status (SES) and children's academic outcomes, and behavioral and emotional development (Burdick-Will et al. 2011; Jones et al. 2011; Kohen et al. 2008; Leventhal and Brooks-Gunn 2000; Pebley and Sastry 2004). Research has also supported neighborhood SES as a factor in a diverse array of adult outcomes, including mental health (Aneshensel and Sucoff 1996; Ross 2000; Wheaton and Clarke 2003), physical health (Acevedo-Garcia 2000; Ross and Mirowsky 2001), drug use (Boardman et al. 2001), economic decision-making and status (Clampet-Lundquist and Massey 2008; Ioannides and Topa 2010), political behavior (Cho et al. 2006; Huckfeldt 1979; McClurg 2006), and even choice of friends (Huckfeldt 1983).

The fundamental assertion behind this "neighborhood effects" body of research is that characteristics of the context in which individuals spend time have important consequences for health and well-being (e.g., Aneshensel and Sucoff 1996; Leventhal and Brooks-Gunn 2000; Pebley and Sastry 2004; Sampson 2011). The frequency and duration of exposure to physical and social environments are important components of describing how people interact with physical context (Jones 2012). One limitation of this research is that virtually all studies to date have focused on the effects of *residential* neighborhoods. However, residential neighborhoods may not adequately represent the full relevant geospatial context to which individuals are regularly exposed (Matthews 2011; Palmer 2012). Sastry et al. (2002) showed that in Los Angeles County, the great majority of individuals travel outside their residential census tract for work, grocery shopping, worship, and health care. Other studies have shown similar results (Vallee et al. 2010; Zenk et al. 2011). The majority of Los Angeles residents travel an average of 8 miles to their workplace = = (Sastry et al. 2002), a distance that can make a huge difference in the local social and physical environment. Employed adults spend a significant portion of their waking hours in and around their workplaces and are likely to be affected by these environments. The same argument can be made for other locations where individuals spend time, such as places of worship and shopping and entertainment venues. Kwan (2012) showed that misspecification of the true geospatial context in a contextual effects study can lead to erroneous findings—both false positives and false negatives. The problem of accurately specifying context has both spatial and temporal components (Kwan 2012). Although researchers typically know the location of survey respondents' homes, they generally do not know the remaining spatial context of exposure, including locations of other places that might be influential—for example, workplace, place of worship, and so on. In addition to uncertainty about *where* survey respondents spend time, researchers also lack information about *how much time* they spend in those places.

Our first aim addresses spatial uncertainty in neighborhood studies. Our goal is to compare the characteristics of residential neighborhoods and the places routinely visited by respondents to determine whether residential neighborhoods adequately represent the characteristics of the larger contexts to which individuals are regularly exposed. We employ a measure of the larger context borrowed from ecological studies: activity spaces. An *activity space*, as we define it, includes the respondent's home location as well as several other places he or she routinely visits.

The concept of activity space is common in ecological studies of animal territories. It also has a well-developed history in human geography and urban studies to describe individual use of urban space (e.g., see Hägerstrand 1967; Horton and Reynolds 1971). Previous studies have examined activity spaces defined by the actual places individuals routinely go (Kestens et al. 2010; Matthews et al. 2005; Schönfelder and Axhausen 2003; Vallee et al. 2010; Wong and Shaw 2011; Zenk et al. 2011). However, these studies have been highly varied in their conceptualizations and measurement of activity spaces. They range from studies that include all locations to which individuals travel in a fixed period of time (e.g., Zenk et al. 2011), which require intensive data collection through GPS monitoring or detailed travel diaries, to studies defining activity spaces based on a subset of routine activities (Kestens et al. 2010; Newsome et al. 1998; Vallee et al. 2010), which have more limited data requirements. We discuss our approach as well as some alternative definitions of activity spaces, in the upcoming Methods section.

A handful of previous studies have examined whether the social environment of residential neighborhoods adequately represents the environment that individuals regularly encounter. For example, Zenk et al. (2011) used data from GPS devices worn by Detroit residents and GIS methods to calculate the characteristics of two types of activity space. Their results indicate that the characteristics of activity spaces were only weakly associated with those of residential neighborhoods. In another example, physical features of residential neighborhoods were compared with those of activity spaces in Montreal and Quebec City (Kestens et al. 2010). The authors employed extensive travel survey data and included the features of all locations where an activity was reported on the previous day. They also found substantial differences between characteristics of residential areas and activity spaces.

Isolation and Contact

Our second goal is to compare the characteristics of activity spaces among individuals of different social class, race/ethnicity, and immigrant status. Growing income segregation can lead to increasing isolation of social class groups from one another. Spatial isolation of the affluent, for example, is likely to increase the concentration of resources in affluent neighborhoods (Acevedo-Garcia et al. 2008; Joseph et al. 2007) because wealthier communities are more effective at obtaining public and private resources, such as street maintenance, schools, policing, farmer's markets, stores, and entertainment. When government budgets are severely strained, increasing residential segregation by income combined with continuing high-quality services for affluent neighborhoods can lead to hollowing out of resources in poor neighborhoods. Moreover, if the affluent are more insulated from the consequences of budget cuts and limited resources because they have no contact with impoverished communities, they may be less likely to see the need for, and to support politically, improvements in public services.

A related consequence of growing income segregation may be declining contact among social class groups. The intergroup contact literature suggests that contact between social groups may decrease prejudice and negative assumptions particularly assumptions—that advantaged groups hold toward out-groups (Ellison et al. 2011; Lee et al. 2004; Pettigrew and Tropp 2008; Tropp and Pettigrew 2005). This literature has traditionally focused on white prejudice toward racial and ethnic minority groups. However, more recent research also has shown positive associations between increased intergroup contact and attitudes toward the homeless, the mentally ill, and the elderly (Lee et al. 2004; Tropp and Pettigrew 2005). These findings suggest possible deleterious effects of isolation on advantaged peoples' attitudes toward other groups, including racial/ethnic out-groups and the poor and working classes.

Our aim is to examine the degree of isolation and contact with their own and other social groups that individuals experience in their activity spaces. We assess the extent to which individuals encounter neighborhoods with income levels, ethnic composition, and immigrant status composition similar to or different from their own individual attributes. Specifically, we assess whether some types of individuals are more likely to encounter greater diversity within their activity spaces than others.

Data

This study is based on data from L.A.FANS (Wave 1), a representative survey of children, families, and neighborhoods in Los Angeles County, California. Los Angeles County is a large, highly diverse region including dense urban areas, older low-density housing tracts, new cul-de-sac–style suburbs and exurbs, and rural areas covering over 4,000 square miles. Of the 9.5 million residents of the county as of 2000, 44 % were Latino, 32 % were white, 13 % were Asian or Pacific Islander, and 9 % were African American. Approximately 1 in 3 were born outside the United States (see upcoming Table 2).

The study design of L.A.FANS is described in detail by Sastry et al. (2006). The survey used a stratified probability sample of 1990 census tracts, with three strata based on the percentage in poverty in 1997: very poor, poor, and nonpoor. Tracts in the very poor and poor strata were oversampled. Based on a complex sampling design, one or two adults were selected from households in 65 home census tracts (Sastry et al. 2006). Households that were unable to complete the interviews in either English or Spanish were excluded from the survey. Response rates were comparable with those of other in-person interview surveys, with 85 % to 89 % of selected respondents completing the survey (depending on the type of respondent) (Sastry and Pebley 2003). For this study, our primary sample is all adults for whom a geocoded home address was available (n = 2,728).

Adults were asked to report the location of key destinations in their lives. We use the responses from up to seven destinations: home residence, workplace (and secondary workplace, if any), primary grocery store, health care provider (for sick care and for well care, separately), and place of worship. The respondents were asked to provide the address or cross streets of each of these locations, and responses were geocoded using ESRI ArcMap (ESRI (Environmental Systems Resource Institute) 2011). After automated geocoding, remaining unmatched destinations were hand-geocoded wherever possible. The match rate for geocoding was 82 %. A total of 9,410 destinations were reported and geocoded across

2,728 adults, with an average of 3.6 geocoded destinations per person, including home addresses.

To identify the census tract in which each point fell, we used ArcMap to overlay the coordinates for all locations on a map of census tracts for the greater Southern California region including Los Angeles, Ventura, Kern, San Bernardino, and Orange Counties. Individual destinations outside these five counties were excluded (*n* = 95). We merged the map of census tracts with the 2000 census social characteristics for tracts in these five counties (U.S. Census Bureau 2000a) to obtain socioeconomic attributes of all tracts in the greater Southern California region.

Our final analytic sample is restricted to those individuals who had at least three geocoded destinations, including their home. This criterion excluded 689 respondents who had only one or two destinations. We also excluded respondents who had missing values for race/ethnicity (*n* = 6) and citizenship (*n* = 57), for a final sample of 1,976 adults.

Activity Space Definition and Measurement

In all analyses, we examine five aggregate socioeconomic characteristics of neighborhoods, as reported in the 2000 U.S. census: the proportions Latino, African American, white, foreign-born, and poor. We construct two types of activity spaces for each respondent in our sample: nodes and polygons. In the first part of the analysis, we compare the social characteristics of respondents' home tracts with those of their nodes and polygons.

Home Tracts—*Home tracts* are defined as the census tracts in which respondents reside. We have information on home tracts for each adult in the sample, and each home tract is one of the sampled 65 L.A.FANS census tracts.

Nodes—Nodes are a concept borrowed from the urban planning and transportation literature (Horton and Reynolds 1971; Kwan 1999; Wong and Shaw 2011). The idea is that a person is exposed to the characteristics of each geographic unit (in this case, a tract) that he/she visits regularly; on the other hand, people have little exposure to the geographic areas between these units (tracts). An example is person who drives a car on the freeway to travel to her workplace. The node model assumes that she will be affected by the social conditions within each node because she spends substantial time interacting with the people and features of the space there. However, she is not affected by the geographic units traversed to get from one node to another because the freeway is elevated from the street. For each person in our sample, we define the tracts in which their destinations are located as the individual's set of nodes. The average number of nodes in our subsample is 4.1, and the average aggregate size of nodes is 8.4 square miles (median 2.4; IQR 2.7).

We create two measures of the characteristics of nodes. First, for each population characteristic, we derive an area-weighted mean across the nodes. For example, for the node average of the proportion Latino, we calculate the area-weighted mean of the proportion Latino across each tract in the individual's set. The average is calculated across reported destinations only; if a particular type of destination was not reported, it is omitted from both the numerator and the denominator.

We also calculate a range measure. To get the range value, we rank each respondent's nodes (from the highest to the lowest value) and take the difference between the highest and the lowest node. The range provides a measure of whether each person is exposed to a narrow or more diverse population within their nodes. Because home tracts are single nodes, we cannot define a range for home tracts. For range, we therefore compare only nodes with polygons.

Polygons—Minimum convex polygons were originally designed for ecological studies of individual territories but have recently been applied to human activity and travel behavior (Buliung and Kanaroglou 2006a, 2006b; Wong and Shaw 2011). In contrast to the node measure, the polygon measure assumes that individuals are exposed both to the places they regularly visit and to the geography in-between these places. This measure captures more information about the interactions between people and the places they travel through as they visit common destinations. For example, a person traveling to work via bus may experience substantial exposure to the census tracts she travels through as she interacts with other passengers on the same bus route, transfers from bus to bus, and stops to run errands. For each person, we create a minimum convex polygon using the reported destinations as the corners (or vertices). The minimum convex polygon is the smallest area that encompasses all the destination points, with no internal angle that exceeds 180 degrees.[1]

Because polygons require at least three vertices, we restrict our sample to only those respondents with at least three geocoded destinations. The average polygon in our sample is 11.1 square miles in area and comprises 4.1 destinations (median 2.4; IQR 8.3 square miles). As for nodes, we calculate two statistics summarizing the social characteristics of these polygons: (1) an area-weighted mean of the characteristics of all the census tracts *partially or completely inside* the respondent's polygon, and (2) the range of each characteristic using the procedure described earlier for nodes, ranking the census tracts partially or completely within the respondent's polygon and taking the difference between the highest-ranked tract and the lowest-ranked tract.

Other Activity Space Definitions—Nodes and polygons are only two of many ways of defining activity spaces. Other common approaches include standard deviation ellipses, kernel density functions, and network paths. Standard deviation ellipses, perhaps the most commonly used method to date, involve calculating a two-dimensional ellipse based on the clustering of an individual's destinations in space (Newsome et al. 1998). Ellipses are drawn by calculating the distance and direction from home to destinations, sometimes weighting destinations by frequency of visits or duration of time spent. Ellipses work best with continuous or point data: for example, in the case of health-care service sites (Sherman et al. 2005) or food outlets (Zenk et al. 2011). The social characteristics data that we use are available for census tract polygons. Approximation of the characteristics of ellipses based on tract data would require the inclusion of sizable areas of tracts, which are only partly included in the ellipse boundaries[2] (see Fig. 1), thus distorting the statistical properties of

[1]Because people might reasonably travel a small distance beyond their destinations—for example, to go to lunch while at work—we also tested versions in which we added a buffer area of one-half or one-quarter mile around the minimum convex polygons. These buffers substantially increased the number of census tracts that were included but had very little influence on the average and range of characteristics.

the shape and compromising its intent to capture an elliptical shape around a central cluster of destinations. Although we encounter the same problem of granularity of our units with polygons, the minimum convex polygon has the virtue of being an arbitrary shape. We also do not have enough destinations per person to reliably calculate ellipses.

No consensus has been reached about which method is best, but comparisons of results among methods have shown that the approach can influence the result (Kestens et al. 2010; Sherman et al. 2005; Zenk et al. 2011). These findings are consistent with ours. The activity spaces approach to defining spatial context is in its infancy, and the results here should be viewed as exploratory.

Geocoding and other data processing for this analysis were performed using ESRI ArcMap 10.0 (ESRI (Environmental Systems Resource Institute) 2011) and Geospatial Modeling Environment 0.5.5 Beta by Spatial Ecology (Beyer 2011).[3] Analyses were performed using Stata 11.0 (StataCorp. 2011).

Analytic Approach

Comparing Residential Neighborhoods With Activity Spaces

In the first part of the analysis, we compare home tracts, nodes, and polygons with one another to discover whether home tracts adequately represent the social conditions experienced by our respondents throughout their daily routines. We employ stacked regression models to estimate the difference between home tract, node, and polygon characteristics. The stacked model approach entails creating a data set with three observations for each person: one observation for the home census tract, one for the node, and one for the polygon. A random effect for individuals allows us to compare the home tract, node, and polygon for each person, and our hierarchical linear regression models also account for the clustering of respondents within the 65 L.A.FANS home census tracts. The difference between the three spatial context definitions is revealed by indicators contrasting home tracts with nodes and polygons.

Dependent Variables—The dependent variables are the mean or range in the attributes characterizing home tracts, nodes, and polygons. We separately model the average and range in five neighborhood social characteristics: the proportions Latino, African American, white, foreign-born, and poor.

Independent Variables—Because the three areas are to some extent spatially overlapping (for each respondent), we expect them to be related. The question is, To what extent the three types of areas *different* from one another? The key independent variables are, therefore, the indicators for whether the social characteristic in question is a home tract, node, or polygon area. In the models of mean characteristics, home tract is the reference

[2]Although one could include only the portion of the tracts that fall inside the polygons, this approach requires the assumption that population is evenly distributed within the tracts, which is not the case, particularly in rural tracts. Sensitivity testing reveals that eliminating tract portions that are outside the polygons has very little effect on the average or range of social characteristics reported here.

[3]In calculating geographic areas, we used the coordinate system 1983 US State Plane California VI. We used the TIGER/Line map of 2000 census tracts provided by the U.S. Census Bureau (2000b).

group, and the coefficient for the indicator variables can be interpreted as the *difference* between the home tract and node, and the home tract and polygon measure. In the case of range measures, the reference group is nodes, and the indicator variable is the difference between the node and polygon ranges.

We control for individual-level characteristics that may affect the size and diversity of individuals' activity spaces, including gender, age, the number of children in the household, education, family income, employment status, whether the respondent has access to a private vehicle, and race/ethnicity.

The difference between home tracts and activity spaces may vary depending on respondents' own characteristics. For example, foreign-born individuals may be more likely than those who are native-born to live in tracts with high proportions of immigrant residents, and they may also concentrate their activities in areas with high proportions of immigrants because they have less ability, opportunity, or reason to travel into other areas. Thus, we would expect smaller differences between the home and activity space characteristics for a foreign-born than a native-born individual. Similarly, if African Americans and Latinos travel farther to work, as the spatial mismatch hypothesis suggests (Stoll and Covington 2012), their home tracts and activity space characteristics are likely to be greater than for other groups. We test for ethnicity-specific effects using interaction terms between individuals' characteristics and the activity space indicator variables. Finally, we control for regression to the mean by including the number of destinations reported and the population density of the area.

Activity Space Characteristics and Individual Characteristics

How frequently do individuals encounter social class and racial/ethnic groups other than their own in their activity spaces? To answer this second research question, we examine differences in the characteristics of activity spaces by individual attributes.

Some individuals may have more-diverse activity spaces than others simply because their activity spaces are larger. Therefore, we begin by investigating whether the size of activity space polygons varies by income, access to a motor vehicle, and other key individual characteristics. The dependent variable is the size of the activity space polygon in square miles. Independent variables are employment status, income, and whether the respondent's household has a private vehicle. We also control for gender, education, race/ethnicity, age, number of children in the home, whether the respondent has moved in the last two years, whether the respondent has friends or family in the area, and the region of Los Angeles County (known as a Service Planning Area (SPA)) in which the respondents' home is located.[4] We use hierarchical linear models with a random effect for home census tract.

Then we examine whether individuals in some social groups are more likely to be exposed to a greater diversity of people compared with those in other social groups. To test this association, we use hierarchical linear regression models in which individual characteristics are used to predict the characteristics of activity spaces (node or polygon separately). Again,

[4]Information on SPAs is available online (http://publichealth.lacounty.gov/chs/SPAMain/ServicePlanningAreas.htm).

a random effect for home census tract is included to account for the clustered sample design. The key independent variables in these models are education, race/ethnicity, family income, employment status, gender, age, number of children in the household, and access to a private vehicle. We separately model a total of 10 neighborhood characteristics: the mean and range in proportions of Latino, African American, white, foreign-born, and poor residents. We also include the number of destinations reported and the population density of the area as controls.

Results

Descriptive statistics (unweighted) for the sample and measures of neighborhood are shown in Table 1. The sample is predominantly female because of specifics of the L.A.FANS sampling strategy. The ethnic distribution, citizenship, and frequency of Spanish language use of the sample are a consequence of both the population composition of Los Angeles County and L.A.FANS' oversample of poor and very poor census tracts. Almost 80 % of sample members have access to a car or other motor vehicle, and more than one-half were working at the time of the survey. The proportion of respondents in our subsample reporting each type of location is also shown.

The last four rows show characteristics of respondents' activity spaces. As described earlier, only respondents reporting three or more points are included in the analysis. On average, the area of home tracts is considerably smaller than the area of individuals' activity spaces. Note the large standard deviations on the land area of activity spaces, indicating considerable variance among respondents.

Comparing Residential Neighborhoods and Activity Spaces

The first goal is to determine whether residential neighborhoods adequately represent the social environments that individuals regularly encounter: that is, to determine how similar the characteristics of home tracts and activity spaces are. In Table 2, we compare characteristics of respondents' home tracts, nodes, and polygons. The last two columns also show the means of the same characteristics for all census tracts in Los Angeles County and in the Greater Los Angeles five-county region. In addition to the mean, Table 2 includes the range of values of the five dependent variables among the tracts that are included in activity spaces, shown in the second row of each cell when they are available.

Compared with activity spaces, home census tracts, on average, have a population that is more likely to be Latino, foreign-born, and below the poverty line. Population density in home tracts is also higher than in activity spaces. Predominantly Latino tracts are more common in the county as a whole because of the relative size of the Latino populations and because Latinos are overrepresented in the L.A.FANS stratified sample. In contrast to many U.S. cities, Los Angeles has very few majority African American tracts but many majority Latino tracts.

Differences in mean characteristics between activity spaces defined by nodes and by polygons are generally modest. However, the range of characteristics differs markedly between the two measures of activity space. In particular, the range is always considerably larger for polygons than for nodes. At least part of the reason is likely to be that polygon-based activity spaces are, on average, larger in area and include more tracts than node-based activity spaces. However, it may also reflect greater correlation between the characteristics of home tracts and destination tracts than between home tracts and areas that must be traversed to reach destinations.

The multivariable models in Table 3 allow us to take account of these and other factors in comparing home tracts and activity spaces by controlling for a wide range of individual characteristics, population density, and the number of destinations reported. In general, the results suggest that home tracts are significantly different from activity spaces in terms of average socioeconomic characteristics—much the same as the bivariate results in Table 2. Only in a few cases is one of the activity space indicators not significantly different from the home tract reference category. Specifically, activity spaces are less Latino and less economically disadvantaged than are home tracts. In all cases except the percentage poverty, nodes and polygons are also significantly different from *each other* although the direction of the difference varies.

To test whether differences between home tracts and activity spaces vary depending on respondents' own characteristics, we estimate a set of interactions in each model between the two activity space dummy variables and individual characteristics. For example, the first model in Table 3—in which the dependent variable is the proportion of the population that is Latino includes interactions between the two activity space dummy variables and whether the respondent is Latino *herself*. In this case, the difference between the proportion of Latinos in home tracts and nodes, and home tracts and polygons, is greater for Latino respondents than for other groups. Nearly all the interaction terms are statistically significant. In models not shown here, we looked at many other interactions between the activity space indicators and individual characteristics and found that these interdependencies are widespread albeit not universal. These results suggest that the magnitude of differences in the attributes of social environments is to some extent contingent on the person's own social characteristics.

We performed a similar analysis comparing the range of characteristics in respondents' nodes with those in their polygon activity spaces (not shown). For all five social characteristics, the range within the polygon was significantly different from that within the nodes. Generally, respondents encountered a greater range of socioeconomic and racial/ethnic groups in polygons than in nodes. Note that we control for the size of the area and the number of destinations reported, so this result is likely not purely an effect of including more data points. We also include the same interaction terms, and again they are generally significant: the difference in range between nodes and polygons partly depends on the individual's own characteristics.

In summary, we find that the characteristics of home tracts in Los Angeles do not represent the social environments to which our adult respondents are regularly exposed, as represented by these two types of activity spaces. Our result indicates that studies using only residential neighborhood do not capture the full context of social and physical exposure and that the theoretical relevance of spatial definitions used in studies of neighborhood effects requires careful attention.

Characteristics of Activity Spaces by Individual Attributes

The second goal of the analysis is to assess the degree of social isolation and contact within activity spaces for individuals with particular social, economic, and demographic characteristics. To do so, we examine variation in activity space characteristics among respondents with different personal attributes, using both polygon- and node-based activity space definitions.

Size of Activity Spaces—Because the size of activity spaces itself varies widely in our sample and is likely to affect the diversity of social groups that individuals encounter, we first examine the determinants of activity space size—specifically, polygon size (in square miles).[5] Table 4 shows the results of two models: the first with a set of basic characteristics, and the second adding information on whether the respondent moved recently and her social contacts. Both models include dummy variables for regions of the county (SPAs). The largest and most significant coefficient is for the dummy variable for the Antelope Valley region, which is the most sparsely populated region of the county.

African American respondents have significantly larger activity spaces than whites, and from Latinos and “other” race/ethnic respondents (direct comparison not shown). Over the past few decades, African Americans have moved out of their traditional core neighborhoods (e.g., South LA) and into ethnically mixed neighborhoods (or in some cases, out of Los Angeles County) (Jargowsky 2003; Ong et al. 2008). Despite residential mobility, many African Americans have retained ties with their former neighborhoods, including church, employment, family, and shopping (Sastry et al. 2004). The larger activity spaces of African American respondents are, at least partly, a reflection of this process. Another hypothesis is that African Americans’ activity spaces are larger because African Americans have to search further for jobs as a result of the history of residential segregation and movement of jobs to outlying areas (Stoll and Covington 2012). However, research on the effects of spatial mismatch on employment and wages suggests that the problem; is less severe in Los Angeles than many other cities; is more of a skills mismatch than a spatial one; and, to the extent that it exists, is actually a transportation problem rather than a distance problem (Liu and Painter 2012; Ong and Miller 2005; Stoll 1999).

More education is significantly associated with larger activity spaces, but few other individual characteristics have consistent relationships to polygon size. Perhaps most surprising is that vehicle ownership is not related to activity space size, perhaps because vehicle ownership is correlated with other variables in the model, such as income and immigrant status.

In Model 2, we add variables representing social ties and relationships that the respondent reports having in her neighborhoods and in Southern California. These additions do not

[5]Because we use census tracts to define nodes and because tract size is determined by population density, the total area of the nodes is highly dependent on the population density of the nodes. Therefore, a similar analysis of node total size is not informative.

markedly change the coefficients on the other variables. However, some are related to activity space size. In particular, respondents who had moved in the two years prior to interview have considerably larger activity spaces than those who did not. Movers may not immediately change locations for all services. Having friends in the neighborhood reduces the size of activity spaces, although this effect is only marginally significant.

Social Isolation Within Activity Spaces—In Table 5 and Figs. 2 and 3, we address the primary research question in the second part of this article: the extent to which individuals encounter social class and racial/ethnic groups other than their own as part of their routine activities. The figures show the predicted characteristics of polygons. The results for node-based activity spaces, which are available in Table S1 of Online Resource 1, are very similar to the polygon-based results. We estimate a separate model for each outcome.

Mean Activity Space Characteristics—Figure 2 shows the predicted *mean* characteristics of activity space polygons based on individual-level race/ethnicity. We derive predicted values by using the coefficients from regression (shown in Table 5). For example, the first panel of Fig. 2 shows the predicted mean proportion Latino in the polygons for individuals who are themselves Latino, white, and African American.[6] This presentation allows us to show the magnitude of difference in activity space characteristics for different groups while accounting for all the variables in the model. However, not all differences (or coefficients for independent variables) are statistically significant (see Table 5). Generally speaking, the population density, the number of destinations reported, education, and race/ethnicity variables are significant predictors of the area-weighted mean polygon characteristics.

Figure 2 shows that an individual's own race/ethnicity is strongly associated with the race/ethnic composition of his/her activity space polygon: for example, the polygons of Latino respondents have significantly higher proportions of Latinos than those of white and African American respondents. Similarly, the activity spaces of whites have higher proportion white than those of Latinos and African Americans, and the activity spaces of African Americans have higher proportion African American than those of Latinos and whites. In everyday life, Latinos' activities take place in predominantly Latino areas (with an average of more than 50 % Latino), whereas neither whites' nor African Americans' activity spaces are composed primarily of their own racial/ethnic group. Figure 2 also illustrates, mirroring the demographic composition of Los Angeles, that the largest racial/ethnic group in all activity spaces is Latino: the average percentage Latino across all groups' activity spaces is about 40 %.

All racial/ethnic groups' activity spaces include a relatively high proportion of foreign-born residents, but as one might expect, the average proportions are higher for Latinos compared

[6]To produce the figures, the predicted values of each outcome variable were calculated using the regression coefficients (shown in Table 5 and Online Resource 1, Table S1) and the means of independent variables, except for the independent variable under consideration, which is set at a specified value. For example, to calculate the percentage Latino in the activity spaces of African American respondents, all *x*-variables were set at their sample means except for the dummy variable for African American race/ethnicity, which was set to 1. For all predictions besides those for race/ethnicity, the race/ethnicity was set to Latino (so the predicted values are for a Latino individual).

with white and African American respondents. Finally, whites' activity spaces include a significantly lower percentage poor, compared with Latinos and African American.

Overall, the pattern shown in Fig. 2 is one of homogeny within activity spaces. Even controlling for education, income, and work status, whites encounter more whites in their activity spaces than do other groups; African Americans encounter more African Americans; and Latinos encounter more Latinos and foreign-born individuals.

A similar pattern of socioeconomic segregation can be seen in the full results for mean activity space characteristics, shown in Table 5. Activity spaces of U.S. citizens are, on average, more advantaged (with lower proportions of minorities and poor) compared with noncitizens. Polygons of less-educated respondents are generally less-advantaged (higher proportions of Latinos, foreign-born, and poor) than those of more-educated respondents. Compared with those who have access to a car, the activity spaces of those who do not are, on average, more likely to be Latino, foreign-born, and in poverty.

These equations take account of many individual-level covariates, including income, labor force participation, and citizenship. Thus, these differences can be interpreted as the independent effect of, for example, having a car on the average characteristics of the area to which respondents are exposed. Although not all contrasts are significant, the pattern shows consistently that advantaged respondents live and travel within more advantaged activity spaces. Figures S1–S5 of Online Resource 1 illustrate predicted values for these contrasts.

In sum, across multiple dimensions, advantaged individuals are exposed to relatively advantaged social environments in their activity space polygons. Furthermore, we demonstrate strong homophily between the respondents' race/ethnicity and SES and the average social attributes of their polygon activity spaces.

Range in Activity Space Characteristics—Next, we investigate the *range* of characteristics of census tracts found in each respondent's activity space. The range measures provide a sense of the diversity of the census tracts that individuals visit in the course of their activities. For example, a person who lives in a working-class census tract and works in an affluent tract would have a greater range value than a person who lives and visits within only affluent tracts. Note that this approach is different from examining overall heterogeneity *among residents* in an individual's activity space, which would involve a comparison of all *individuals* within the space. Instead, our variable measures the heterogeneity *among tracts* that a respondent routinely visits.

Because the range is likely to be affected by the number of tracts included in the activity space, we control for the number of locations defining the activity space. As Table 5 shows, many of the individual-level characteristics predict the range in social characteristics in activity space polygons. The number of children is negatively associated with range in all five polygon characteristics; more children in the family are associated with a narrower range of places in the activity space. Education and employment are associated with a greater range in racial/ethnic composition, and citizenship is associated with smaller ranges several social characteristics. Figures S6–S10 (Online Resource 1) illustrate the predicted values for many other contrasts.

Perhaps the most important results from our range measures are the coefficients for the racial/ethnic groups. Results are illustrated in Fig. 3 with predicted values for the range of characteristics within activity space polygons. African American respondents appear to have the most highly variable activity spaces of any of the racial/ethnic groups—a finding that holds across all five dimensions. As described earlier, these results may be linked to the movement of many African Americans out of traditionally African American neighborhoods in Los Angeles. Those who left may return regularly to work, to places of worship and stores, and to visit friends and family. All these factors would contribute to a greater range in the characteristics of African American activity spaces. In general, the smallest ranges are in whites' activity spaces. Compared with whites and across nearly every dimension, all other racial/ethnic groups experience greater heterogeneity in their activity spaces. This result—along with the finding that the activity spaces of whites are, on average, more advantaged—hints at a social isolation of whites in Los Angeles that cuts across important daily destinations.

Overall, we see a diverse pattern for range outcomes. Perhaps surprisingly, more-advantaged people do not visit narrower ranges of places across the board, although some individual contrasts suggest that there are important differences in range by SES. The largest and most significant differences we see for range outcomes are by race/ethnicity: African Americans and Latinos experience a considerably broader range of places than do whites, except when it comes to the range in proportion white itself, suggesting that whites are constrained to a narrower sociospatial context than are other groups. African American respondents, on the other hand, experiences the broadest range of places in their activity spaces.

Discussion

Our goal in this article was to answer two questions. First, do residential census tracts adequately represent the social environments in which individuals routinely move? In general, the answer to this question is no. The characteristics of activity spaces, as defined in this article, are significantly different from the characteristics of respondents' home census tracts. We would expect activity spaces or any area around—but larger than—a home tract to have social characteristics more like the mean characteristics in the county as a whole, purely through regression to the mean. We attempted to control for this effect by including the number of destinations reported and the population density of the area in the models where it is an important concern. However, if regression to the mean plays a significant role in the differences between home tracts and activity spaces, this discrepancy represents a reality: people are exposed to a social landscape that is actually more diverse than their home census tract. Individuals' activity spaces are often quite different than home tracts. Consistent with our results, Ellis et al. (2004) also found more between-group contact when comparing home census tracts with work census tracts for Los Angeles adults.

A key empirical question for future research is whether individual behavior and outcomes are more influenced by social conditions in activity spaces or home tracts. Along with a handful of previous studies (Crowder and South 2011; Inagami et al. 2007; Matthews 2011; Sastry et al. 2004), our results suggest that lack of information about the universe of places in which respondents spend time could have an important influence on causal inference about neighborhood effects in general. Researchers interested in the effects of individuals' social environments on behavior and well-being need to consider areas of exposure beyond home neighborhoods. Many people spend the majority of their (nonsleep) time and have most of their social contacts with people in locations other than where they live. Research in this area is only beginning to consider this larger environment.

Our second question is how individual characteristics are associated with the attributes of activity spaces. In other words, are some groups more isolated from others in their day-to-day life? We found that individuals' own characteristics are closely associated with those of their activity spaces: for example, whites' activity spaces have a higher proportion of whites, African Americans' activity spaces have a higher proportion of African Americans, and so on. The activity spaces of respondents with more years of schooling—a measure of socioeconomic advantage—are more advantaged across several dimensions compared with activity spaces of other respondents. This is evidence of multidimensional socioeconomic segregation that extends beyond the residential neighborhood and into the other places adults visit in the course of a typical week.

Results from our range measures show that some groups have a broader range of places within their activity spaces, or are less isolated to contact within their own group. African Americans are in some sense the least socially isolated group in Los Angeles because they tend to move among places with highly variable racial/ethnic composition and SES. Whites have the lowest ranges in activity space characteristics and are far more likely than any other group to have activity spaces with a sizeable proportion of whites. Latinos are also isolated in a sense because their activity spaces have very high average proportions Latino and foreign-born; however, this is in part a product of the overall demographic makeup of the region. The range of places in activity spaces of Latinos is larger than that of whites along several dimensions.

Although this article makes several important contributions, our work on activity spaces is exploratory and limited in several ways. First, we used definitions of *activity space* (and indeed, of *residential neighborhood*) that have limited intrinsic meaning. The destinations on which the activity space are based are also limited to seven places, many of which (e.g., grocery store) allowed only a single response. Our respondents' true geospatial context is necessarily more complex than the data allowed us to measure. However, when we performed sensitivity tests with a broader range of destinations (up to 27; results not shown), the increased detail did not change our conclusions. Another important limitation is that we did not address the problem of temporal uncertainty: that is, determining how much time an individual spends in each place. In future work, we plan to explore this temporal aspect of contextual uncertainty using data from L.A.FANS. Individual-centered and continuous-location data, such as that collected with GPS tracking, could help to identify true activity paths of individuals and would provide much richer data to address problems of both spatial and temporal uncertainty (Palmer et al. 2013).

An additional limitation is that we have incomplete information about the *actual* social context our respondents encounter in their activity spaces. The only data available for tracts are based on people who live in each tract. However, the population of a place (and its characteristics) may vary considerably: for example, from daytime to nighttime. In addition, we do not know the extent of interaction that occurs between individuals and the people in their activity spaces. For example, a worker in a downtown high-rise building may not interact on a typical workday with anyone living in the tract where the high-rise is located. In contrast, a housekeeper in an affluent home may interact closely with permanent residents of the tract in which she works. Although collection of data on levels and types of social interaction within activity spaces would be enormously complex and potentially quite intrusive, it would provide a more complete understanding of sociospatial context and how it varies over the course of a day.

Finally, this article relies exclusively on one wave of the L.A.FANS data. An important issue that can be addressed with subsequent waves of L.A.FANS is how activity spaces and their characteristics change over time and throughout the life cycle. Important period-specific changes, such as the continuing out-migration of African Americans from traditionally African American neighborhoods, the slowdown in Mexican migration to the United States, the ongoing development of rail-based public transit, and the economic recession and evolving recovery are likely to have changed Angelenos' use of space over the past decade. At the same time, cohorts are likely to change their use of space as they age; for example, young adults may have larger and more varied activity spaces, while parents of small children may travel in more regular and limited patterns. Changes in activity space over time are an important topic for future research.

In summary, our results suggest that activity spaces provide a different picture of social exposures than home census tracts, which are typically used in neighborhood effects research. Furthermore, the picture of social exposure varies based on the definition of activity space employed. Researchers investigating the effects of social and physical characteristics of place on individuals should be wary of assuming that residential neighborhoods represent exposures accurately and should carefully consider the true causally relevant context for their study.

Adult respondents in L.A.FANS-1 experience a great deal of isolation from other social groups, based on the characteristics of their activity spaces. On average, advantaged respondents travel within advantaged activity spaces; conversely, disadvantaged respondents have disadvantaged activity spaces. An extensive body of evidence has shown that this is true in residential neighborhoods, but we have shown that it is also true when we account for up to seven places that adults routinely visit—suggesting that, unsurprisingly, the concept of "segregation" extends to the dynamic patterning of how people travel within the broader urban sociospatial context.

The results also provide important insights into the social dynamics of Los Angeles County, which is the largest county by population and contains the second-largest city in the United States. The relative social isolation of whites is not unique to this urban area. It is also not surprising, given residential segregation patterns, to find that well-educated people (i.e., those with more than a high school diploma) have activity spaces with higher proportions white. Also not surprising is our finding that the Latino population is relatively isolated in the sense that they encounter primarily other Latinos in their activity spaces. However, unlike many cities, a major reason for Latino isolation in Los Angeles is that they are by far the largest racial/ethnic group there. Thus, for whites, African Americans, and Latinos, the predominant ethnic group in their activity space are Latinos. Particularly intriguing, and a break from patterns in other cities and from Los Angeles' past, is the experience of African American Angelenos, who experience considerably more diversity in their activity spaces than do whites and Latinos.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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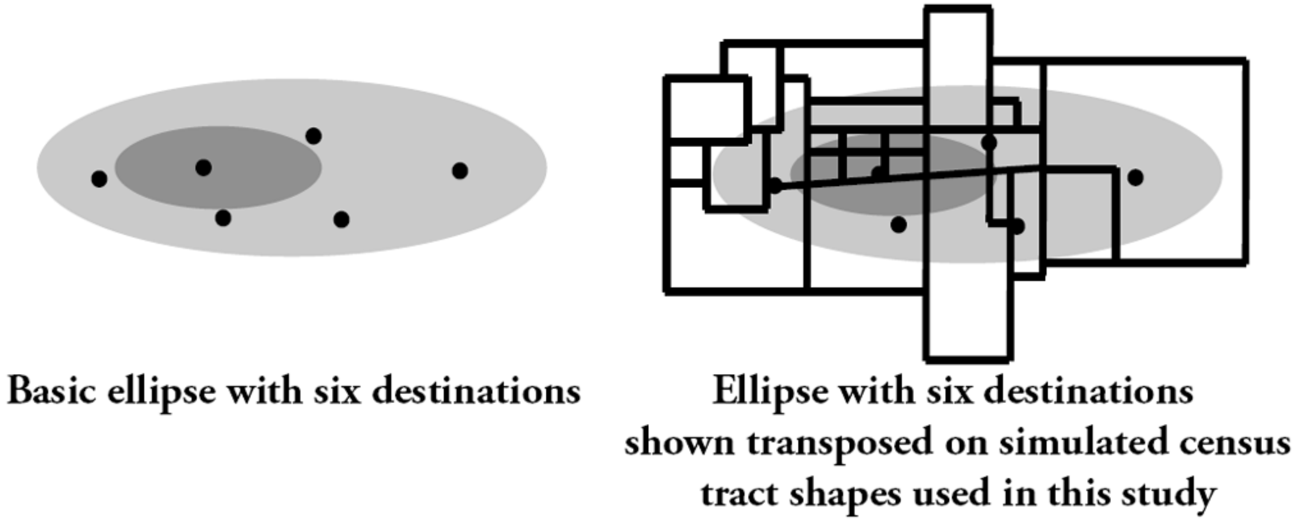

Fig. 1.
Illustration of ellipses with discontinuous underlying data

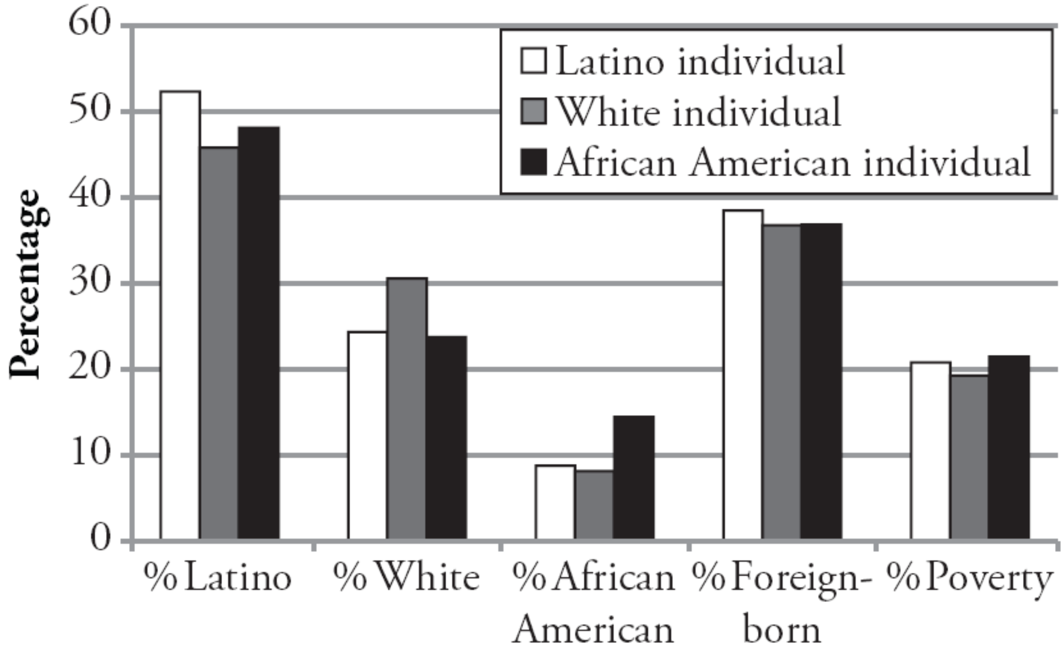

Fig. 2.
Predicted *mean* activity space polygon characteristics by individual race/ethnicity

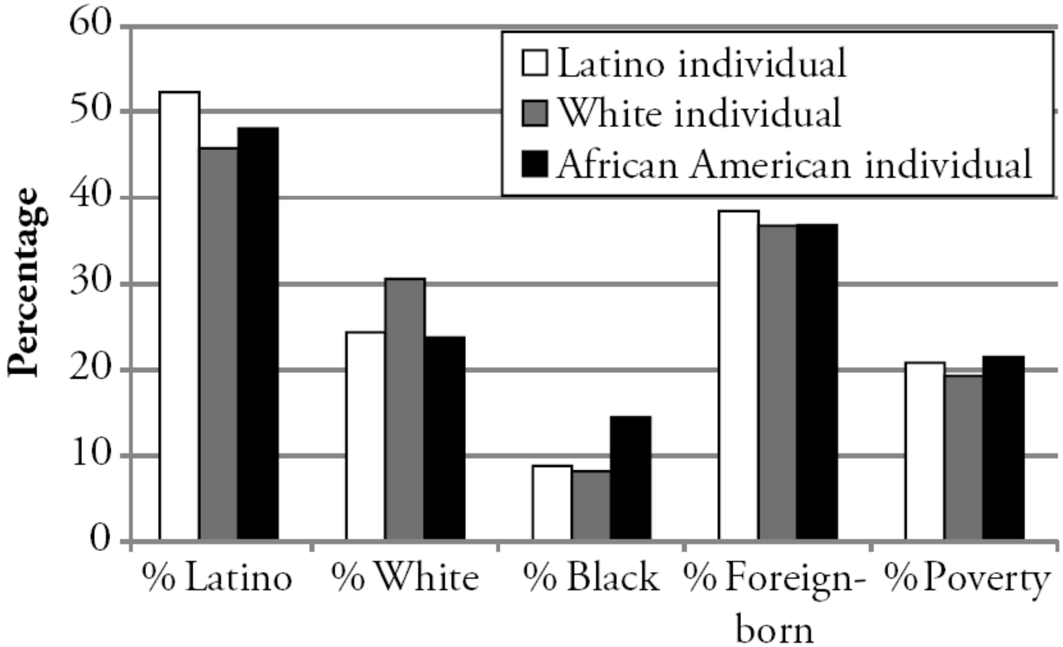

Fig. 3.
Predicted *range* activity space polygon characteristics by individual race/ethnicity

Table 1

Descriptive statistics for the sample (*n* = 1,976, unweighted)

	% or Mean	(SD)
Female Gender (%)	75.0	
Education (mean years)	12.6	(4.4)
Number of Children in Household (mean)	1.7	(1.4)
Race/Ethnicity (%)		
Latino	52.0	
White	28.0	
African American	11.0	
Asian	7.0	
Pacific Islander	0.0	
Native American	1.0	
Other	0.0	
U.S. Citizen (%)	66.0	
Spanish-Language Interview (%)	34.0	
Has a Vehicle (%)	79.0	
Moved in the Last 2 Years (%)	27.0	
Currently Working (%)	64.0	
Age (mean years)	40.0	(13.4)
Family Income ($1,000s, mean)	57.3	(99.5)
% of Respondent Sample With Location Reported		
Home	100.0	
Grocery store	97.0	
Health care facility for sick care	73.0	
Primary employer	59.0	
Place of worship	38.0	
Secondary employer	28.0	
Health care facility for well care	12.0	
Number of Destinations Reported (mean)	4.1	(0.9)
Area of Home Tracts (mean sq. mi.)	1.5	(9.3)
Area of Activity Space Nodes (mean sq. mi.)	8.4	(37.2)
Area of Activity Space Polygons (mean sq. mi.)	11.1	(34.8)

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Table 2

Descriptive Statistics of Home Tracts, Activity Spaces, and Study Area, From Census 2000

Characteristic	Home Tracts Mean (SD)		Nodes Mean (SD) Range (SD)		Polygons Mean (SD) Range (SD)		LA County Tracts Mean (SD)		Five-County Area Tracts Mean (SD)	
Observations	1,976 adults		1,976 adults		1,976 adults		2,055 tracts		3,207 tracts	
Area (square miles)	1.5	(9.3)	8.4	(37.2)	11.1	(34.8)	2.0	(13.4)[a]	10.9	(162.7)[b]
Population Density (population/sq. m., 1000s)	14.7	(11.0)	10.1	(7.5)	10.1	(6.8)	12.5	(10.9)	10.1	(9.8)
Population	5,403	(2,128)	20,165	(6,851)	169,982	(266,265)	4,633	(1,782)[c]	4,833	(2,254)[d]
% Latino	53.0	(30.0)	46.5	(26.2)	48.4	(25.2)	43.5	(29.6)	39.7	(28.8)
			34.4	(22.9)	55.9	(28.2)				
% White	25.5	(26.3)	30.0	(24.0)	26.7	(22.5)	32.0	(28.5)	39.1	(29.4)
			27.6	(22.7)	43.7	(28.0)				
% African American	8.2	(10.5)	8.6	(11.0)	9.5	(11.7)	9.2	(15.6)	7.0	(13.1)
			12.8	(16.0)	26.2	(26.5)				
% Foreign-born	39.4	(15.3)	36.0	(13.1)	37.3	(12.4)	35.5	(16.4)	30.6	(17.1)
			21.1	(13.2)	37.5	(19.5)				
% Poverty	22.0	(14.1)	19.1	(11.5)	20.0	(11.0)	17.9	(13.0)	15.7	(12.4)
			17.7	(12.5)	34.5	(21.4)				

[a] Total area of L.A. County: 4,102 square miles.

[b] Total area of five-county area: 35,049 square miles.

[c] Total population of L.A. County = 9,519,96.

[d] Total population of five-county area = 15,499,319.

Table 3

Stacked regression models comparing the *average* characteristics of home tracts, nodes, and polygons

	% Latino	% White	% African American	% Foreign-born	% Poverty
Home Tracts Indicator (ref.)					
Nodes Indicator	−3.06***	6.17***	0.37	−5.60***	−21.18***
Polygon Indicator	−0.23[a]	3.66***[a]	1.15***[a]	−4.14***[a]	−22.58***
Population Density of Area (1,000s)	0.61***	−0.59***	0.02	0.56***	0.47***
Number of Destinations Reported	−0.80***	0.27	0.44***	−0.45***	−0.24*
Female	0.03	0.23	−0.14	0.05	−0.30
Age (years)	−0.01	0.00	0.01	−0.02*	−0.01
Number of Children in Household	0.35*	−0.24*	0.06	0.02	0.08
Education (years)	−0.27***	0.17***	0.07*	−0.11***	−0.08**
Family Income (logged)	0.08	0.28	−0.31**	0.02	−1.45***
Currently Working	−0.35	0.29	−0. 22	0.09	−0.07
Household Has a Personal Vehicle	−1.37**	0.99*	0. 09	−0.55*	−0.62**
White	(ref.)	0.0784***	(ref.)	(ref.)	(ref.)
Latino	8.04***	(ref.)	0.32	0.93**	0.69*
African American	0.71	−0.30	2.34***	0.08	1.21***
Other Race/Ethnicity	0.16	1.44*	0.56	−0.04	−0.11
Citizen	−0.96	0.95*	−0.26	−2.41***	−0.61**
Polygon × Latino	−8.42***				
Node × Latino	−6.57***				
Polygon × White		−8.73***			
Node × White		−6.05***			
Polygon × African American			1.76**		
Node × African American			0.35		
Polygon × Citizen				3.19***	
Node × Citizen				3.42***	

	% Latino	% White	% African American	% Foreign-born	% Poverty
Polygon × Log Family Income					1.99***
Node × Log Family Income					1.77***
Constant	51.62***	20.74***	7.85***	39.26***	5.43***
Observations	5,928	5,928	5,928	5,928	5,928
Level 1 Groups (individuals)	1,976	1,976	1,976	1,976	1,976
Level 2 Groups (home neighborhoods)	65	65	65	65	65

[a]Coefficient is significantly different from the indicator for node value at $\alpha = .05$.

* $p < .05$;

** $p < .01$;

*** $p < .001$

Table 4

Size of polygon activity space (square miles) as a function of individual characteristics

	Model 1, *b*	**Model 2, *b***
Female	−3.3083	−3.3202
Education (years)	0.5967*	0.5970*
White (ref.)		
Latino	−1.1256	0.5404
African American	10.5096***	10.4300**
Other Race/Ethnicity	2.5772	6.2112
U.S. Citizen	−1.9174	−0.8374
Age (years)	−0.1359*	−0.0707
Family Income (logged)	0.5906	1.1008
Currently Working	3.1369	4.3587*
Household Has a Personal Vehicle	0.5603	1.6085
Number of Children in Household	−0.7294	−0.7605
SPA 1: Antelope Valley	60.8382***	69.5892***
SPA 2: San Fernando Valley	3.8007	2.9729
SPA 3: San Gabriel Valley	6.4825	6.1882
SPA 4: Metro (ref.)		
SPA 5: West	−1.9893	−3.0603
SPA 6: South	1.6466	1.3064
SPA 7: East	7.1247	6.0451
SPA 8: South Bay	5.3383	3.8689
Moved in Last Two Years		6.4535**
Any Family in the Neighborhood (yes/no)		0.2066
Any Friends in the Neighborhood (yes/no)		−4.7245*
Any Family in Southern California (yes/no)		−0.4633
Constant	−0.0985	−9.266
N	1,976	1,579

* $p < .05$;

** $p < .01$;

*** $p < .001$

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Table 5

Average and range in polygon characteristics as a function of individual characteristics

	% Latino		% White		% African American		% Foreign-born		% Poverty	
	Mean	**Range**	**Mean**	**Range**	**Mean**	**Range**	**Mean**	**Range**	**Mean**	**Range**
Population Density (1,000s)	1.04***	−0.73***	−0.97***	−1.36***	0.04	−0.025**	0.84***	−0.91***	0.75***	−0.31***
Number of Destinations Reported	−0.63	9.09***	−0.32	7.21***	1.00***	6.55***	−0.29	6.39***	−0.09	6.59***
Female	−0.34	−2.71*	0.70	−0.74	−0.64	−2.26*	0.23	−1.48	−0.53	−1.83
Age (years)	−0.02	−0.02	0.00	−0.01	0.00	0.01	−0.02*	−0.02	−0.02*	−0.03
Number of Children in Household	0.40	−1.18**	−0.31	−1.13**	0.06	−0.88*	0.13	−0.74*	0.24*	−0.67*
Education (years)	−0.44***	0.13	0.28**	0.35*	0.06	0.30*	−0.13**	0.19	−0.17***	0.06
Family Income (logged)	0.03	−0.14	0.43	0.58	−0.42*	−0.30	0.10	0.26	−0.20	0.55
Currently Working	−0.75	2.82*	0.23	2.21	−0.03	1.48	0.08	1.11	−0.52	1.63
Household Has a Personal Vehicle	−2.64**	5.11***	1.35	4.88***	0.62	2.80*	−1.29***	2.43*	−1.38***	2.00
White (ref.)										
Latino	6.49***	5.80**	−6.21***	−0.12	0.63	4.60**	1.72***	3.31**	1.53***	5.61***
African American	2.28	14.16***	−6.83***	4.93*	6.32***	18.29***	0.08	8.57***	2.21***	13.80***
Other Race/Ethnicity	1.29	4.49	−2.79*	1.74	0.58	1.80	0.12	2.78	−0.05	3.76*
U.S. Citizen	−1.32	−1.20	1.79*	0.94	−0.65	−3.39**	−0.66	−3.18**	−1.01**	−2.81*
Constant	46.94***	20.93**	31.15***	13.82*	7.74**	−1.45	31.78***	15.37**	19.25***	2.84
N	1,976	1,976	1,976	1,976	1,976	1,976	1,976	1,976	1,976	1,976

* $p < .05$;

** $p < .01$;

*** $p < .001$