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

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April 18, 2012

For presentation at the Annual Meeting of the Population Association of America
May 2-5 2012
San Francisco, CA
Session 659: Reconceptualizing Neighborhood Contexts: Measuring Contexts and Processes

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 (Cho, Gimpel et al. 2006; Entwisle 2007; Fauth, Leventhal et al. 2007; Covington 2009; Braveman, Cubbin et al. 2010; Sastry and Pebley 2010). This literature focuses largely on residential neighborhoods, but adults and children are generally exposed to other places in the course of their daily lives—at school, at work, shopping, etc. Thus, studies of residential neighborhoods consider only a subset of potential environmental influences on individuals.

In this paper, we examine the characteristics of adults' "activity spaces," i.e., spaces defined by locations that individuals visit regularly, in Los Angeles County, California. Activity spaces include, but often extend well beyond, residential neighborhoods. We use unusual data from the 2000-2001 Los Angeles Family and Neighborhood Survey - Wave I (L.A.FANS-1) on geographic coordinates[1] for adults' homes, grocery stores, work places, health care facilities, and places of worship which they regularly visit or 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.

Our study has two distinct goals. First, we compare the characteristics of individuals' activity spaces to those of their residential neighborhoods. Our goal is to determine whether or not residential neighborhoods adequately represent the social conditions (e.g., poverty, affluence, ethnic composition) to which adults are exposed in their regular activities. For example, Wong and Shaw (2011) and Lee, Reardon et al. (2008) argue that activity spaces are better reflections of the degree of race/ethnic and income segregation that individuals experience because they reflect the full range of daily experience. If activity spaces and residential neighborhoods differ substantially from each other, then the multitude of studies on residential neighborhood effects may be missing an important part of the picture, as some have suggested (Sastry, Pebley et al. 2004; Inagami, Cohen et al. 2007; Crowder and South 2011; Matthews 2011).

Our second goal is to compare the characteristics of activity spaces among individuals of different social classes, race/ethnicities, and immigrant statuses. The objective is to assess how frequently individuals encounter social class and race/ethnic groups other than their own, as part of their routine activities. As described below, contact among social groups may have important effects on a person's assumptions about, and attitudes toward, other social groups and how they live (Pettigrew 2008; Rocha and Espino 2010; Chaskin and Joseph 2011; Ellison, Shin et al. 2011). For example, affluent West Los Angeles residents may glimpse poor Latino South and East Los Angeles neighborhoods only from elevated freeways. By contrast, some low income immigrants are extensively exposed to affluent neighborhoods through gardening, housekeeping, and childcare jobs. Assumptions and attitudes about other groups may be important for social solidarity, political behavior, and many other aspects of urban life. In this paper we examine the degree of contact or isolation across social groups in Los Angeles by investigating the social characteristics of individuals' activity spaces as a function of individuals' attributes.

We find that, generally, individuals are exposed to a broader range of people and conditions in their activity spaces than in their home census tracts. However, the characteristics of both home tracts and activity spaces are closely associated with individual characteristics–e.g., Latinos are much more likely to be exposed to other Latinos; the poor are much more likely to be exposed to other poor.

[1] Data on geographic coordinates are provided by the L.A.FANS project as restricted data. See http://lasurvey.rand.org/data/restricted/ for more information.

That this is true even when we use activity spaces suggests that most people experience substantial racial and economic segregation across the range of spaces in their daily lives, not just in their home tract. We also find that people who are employed, those with more education, and non-whites experience a broader range of people in the course of their daily lives, compared to others. Non-Hispanic whites[2] are exposed to strikingly less race/ethnic diversity than all other groups.

BACKGROUND

Since the 1970s, the US has experienced both increasing income inequality and growing spatial segregation by family income in metropolitan areas (Reardon and Bischoff 2011). Mixed income neighborhoods have become rarer, and both affluent and poor enclaves have become more common, although the affluent are more likely to be segregated from other groups than are the poor. Between 2000 and 2007, income segregation *among* black and Latino families increased sharply and these two groups are now much more segregated by income than whites (Reardon and Bischoff 2011). Although black-white segregation itself has declined since 1990, African Americans remain the most segregated race/ethnic group and Latino-white and Asian-white segregation increased between 1990 and 2010 (Frey 2012).

Neighborhood Effects

Growing income segregation in metro areas heightens the importance of research on the welfare consequences of concentrated poor and affluent neighborhoods. In the past two decades, observational and experimental studies have found associations between neighborhood socioeconomic status and children's academic outcomes, and behavioral and emotional development (Leventhal and Brooks-Gunn 2000; Pebley and Sastry 2004; Kohen, Leventhal et al. 2008; Burdick-Will, Ludwig et al. 2011). Research has also supported neighborhood socioeconomic status 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, Finch et al. 2001), economic decision making and status (Clampet-Lundquist and Massey 2008; Ioannides and Topa 2010), political behavior (Huckfeldt 1979; Cho, Gimpel et al. 2006; McClurg 2006), and even choice of friends (Huckfeldt 1983).

Virtually all of these studies have focused on the effects of the *residential* neighborhoods. However, when potentially confounding individual, family, and household characteristics are held constant using appropriate data and models, the size of residential neighborhood effects often modest (Pebley and Sastry 2004; Entwisle 2007; Galster 2011). Although these findings may in fact represent reality, there are several reasons to think that studies to date have understated the importance of neighborhoods, including: reliance on cross-sectional data, inadequate accounting for residential moves in longitudinal data, homogeneous samples, and, in experimental research, selective treatment compliance (Entwisle 2007; Clampet-Lundquist and Massey 2008; Sampson 2008).

Another limitation of most previous research is that residential neighborhoods may not adequately represent the social and physical environments to which individuals are regularly exposed (Matthews 2011). This is true regardless of how residential neighborhoods are defined. For example, Sastry, Pebley et al. (2004) show that in Los Angeles County the great majority of individuals travel outside their residential census tract for work, grocery shopping, worship, and health care. In the case of workplaces, the majority travel more than two tracts away from their residential tract or an average of eight miles. Eight miles can make a huge difference in the social and physical environment, e.g.,

[2] In the paper we refer to non-Hispanic whites as whites and to non-Hispanic blacks as blacks. We also use Latino and Hispanic interchangeably.

affluent Beverly Hills is only 6 miles from low-income Pico-Union. Employed adults spend a significant portion of their waking hours in and around their work places and are likely to be affected by these environments. The same argument can be made for other locations that individuals spend time, such as places of worship and shopping and entertainment venues. Other studies have also shown that individuals travel frequently outside of their residential neighborhoods (Vallee, Cadot et al. 2010; Zenk, Schulz et al. 2011). In this paper, we compare the characteristics of residential neighborhoods and activity spaces to determine whether residential neighborhoods adequately represent the larger environments to which individuals are exposed on a regular basis.

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 (for example, see Ha□gerstrand (1967); Horton and Reynolds (1971)). In space-time geography, activity spaces are often seen as constraints on the space that an individual is capable of traveling in a given time, i.e., as *potential* activity spaces (Newsome, Walcott et al. 1998; Matthews 2011). Other studies have examined activity spaces defined by the actual places individuals go on a routine basis (Schönfelder and Axhausen 2003; Matthews, Detwiler et al. 2005; Kestens, Lebel et al. 2010; Vallee, Cadot et al. 2010; Wong and Shaw 2011; Zenk, Schulz et al. 2011) – the approach used in this paper. Previous studies are 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, Schulz et al. 2011) -- and therefore require intensive data collection through GPS monitoring or detailed travel diaries – to studies defining activity spaces based on a subset of routine activities (Newsome, Walcott et al. 1998; Kestens, Lebel et al. 2010; Vallee, Cadot et al. 2010) – which have more limited data requirements. We discuss alternative definitions of activity space in the Methods section below.

A handful of previous studies have examined whether the social environment of residential neighborhoods adequately represent the environment that individuals encounter on a regular basis. For example, in a study of Detroit residents, Zenk, Schulz et al. (2011) used data from GPS devices worn by respondents and GIS methods to calculate the characteristics of two definitions of activity space: one-standard-deviation ellipses and daily path areas. They contrasted these activity spaces with residential neighborhoods (defined as a 0.5 mile buffer around the centroid of the census block in which respondents lived) and showed 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 to those of activity spaces in Montreal and Quebec City (Kestens, Lebel et al. 2010). The authors employ extensive travel survey data and include the features of all locations where an activity was reported on the previous day. They also find substantial differences between residential areas and those of activity spaces.

Isolation and Contact

Growing income segregation can also lead to increasing isolation of social class groups from each other. Spatial isolation of the affluent, for example, is likely to increase the concentration of resources in affluent neighborhoods (Joseph, Chaskin et al. 2007; Acevedo-Garcia, Osypuk et al. 2008), because wealthier communities are more effective at obtaining public and private resources. Resources include better public services (e.g., street maintenance, trash removal, policing, schools, parks and recreation, libraries) and also private commercial services which are sometimes substitutes for limited public services (e.g., security services, private recreational clubs, farmers' markets, and a diversity of 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, 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, particularly of advantaged groups toward out-groups (Lee, Farrell et al. 2004; Tropp and Pettigrew 2005; Pettigrew and Tropp 2008; Ellison, Shin et al. 2011). This literature has traditionally focused on white prejudice toward racial and ethnic minority groups and has suffered from methodological limitations. However, more recent research which shows positive associations between contact and attitudes toward the homeless, the mentally ill and the elderly (Lee, Farrell et al. 2004; Tropp and Pettigrew 2005) suggests that there could be similar effects for attitudes toward outgroups not defined by race/ethnicity, such as the poor and working class. Despite the emphasis of previous research on interpersonal interactions, other types of contact, including observation of the out-group in public settings, exposure to out-group neighborhoods, or media portraits of out-groups, may shape attitudes about these groups (Lee, Farrell et al. 2004; Ellison, Shin et al. 2011). Conversely, increased exposure to outgroups may simply establish or confirm the beliefs of advantaged individuals about members of these groups.

Determining the consequences of intergroup contact or isolation is outside the scope of this paper. Instead, we assess the extent to which individuals encounter neighborhoods with income levels, ethnic composition, and immigrant status composition different from their own. Specifically, we compare the social composition of activity spaces for individuals of different backgrounds to determine whether some types of individuals are predisposed to encounter a wider range of neighborhoods than are other people.

DATA

This study is based on data from the Los Angeles Family and Neighborhood Survey, Wave 1 (L.A.FANS-1) conducted in 2000-2001. L.A.FANS-1 is a representative survey of the 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 spread over 4,083 square miles. Of the 9.3 million residents of the county as of 2000, 45% were Latino, 31% were white, 13% were Asian or Pacific Islander, and 10% were African American. About 30% were not born in the U.S. (Sastry, Ghosh-Dastidar et al. 2006).

L.A.FANS was designed for the study of neighborhood effects on individuals. The design is described in detail by Sastry, Ghosh-Dastidar et al. (2006). The survey was based on a stratified probability sample of 1990 census tracts. Three strata were defined based on the percent in poverty in 1997: very poor (tracts in the top 10% of the poverty distribution), poor (those in the next 30%), and non-poor (bottom 60%). Tracts in the very poor and poor strata were oversampled. In each tract, census blocks were sampled with probability proportional to population size, and households were randomly selected from within blocks. The survey sought to interview 50 households in each of 65 census tracts. Households that were unable to complete the interviews in either English or Spanish were excluded from the survey. Response rates were comparable to those of other in-person interview surveys, with 85-89% of selected respondents completing the survey (depending on the type of respondent) (Sastry and Pebley 2003). Within each selected household, one or two adults were selected for inclusion in the sample according to a complex sampling design (Sastry, Ghosh-Dastidar et al. 2006). For this study, we use all adults for whom a home address was available (n=2,728).

The L.A.FANS-1 data contain individual-level information about education, race & ethnicity, age, gender, employment status, the number of children in the household, and whether the respondent has access to a personal vehicle. We use these as independent variables in our models.

Adults were also asked to report the location of up to seven key destinations in their lives: home residence, place of work (and secondary place of work, if any), primary grocery store, health care provider (for sick care and well care, separately), and place of worship. They were asked to provide the address or cross streets of each of these locations, and these responses were geocoded using ESRI ArcMap (ESRI (Environmental Systems Resource Institute) 2010). 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.

We used the results of geocoding in ArcMap to produce longitude and latitude coordinates. To identify the census tract in which each point fell, we used ArcMap to overlay the coordinates 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 not included in this analysis (n=95). We then merged the map of tracts with the 2000 decennial Census social characteristics for tracts (U.S. Census Bureau 2000) and the Los Angeles Neighborhood and Social Characteristics database (NSC)[3] to produce a database of the social characteristics of all census 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 (n=2,047). We also excluded respondents who had missing values for race/ethnicity (n=6), for a final sample of 2,041 adults.

Activity Space Definition and Measurement

In all analyses, we examine six characteristics of neighborhoods, as reported in the 2000 US census: the proportions Latino, black, white, foreign born, and poor; and median household income. We use self-reports of the locations of destinations to which respondents routinely travel to compare the social characteristics of respondents' home tracts to those of two types of activity spaces: nodes and polygons.

Home Tracts
Home tracts are defined as the census tracts in which respondents reside. We have home tracts for 2,728 people, one for each adult in the sample. Each 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, tract) which he/she visits regularly; on the other hand, people have little exposure to the geographic areas between these units (tracts). An extreme example is an individual who drives a car on the freeway -- freeways are typically elevated above the surface streets -- to travel to each of their regular locations (nodes). The node model assumes that this individual will be affected by the social conditions within each node because they spend substantial time there, but not by the conditions of geographic units traversed to get from one node to another. For each person in our sample, we identify the tracts in which their destinations are located

[3] Available from www.lasurvey.rand.org.

as their set of nodes. The average number of destinations in our subsample is 4.1, and the average aggregate size of nodes is 8.2 square miles.

We calculate an area-weighted mean for each population characteristic across the nodes. The average is calculated across reported destinations only; if a particular type of destination was not reported then it is omitted from both the numerator and the denominator. 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. We also calculate a range of exposure across the nodes. To get the range value, we rank the set of nodes for each person from the highest to the lowest proportion Latino. We take the difference between the highest and the lowest node as the range of social characteristics to which this person is exposed. The range provides a measure of whether each person is exposed to a narrow or more diverse part of the population.

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 2006; Buliung and Kanaroglou 2006; Wong and Shaw 2011). In contrast to the node measure, the polygon measure assumes that individuals are exposed to both the tracts which they regularly visit and to the geography in between these tracts. This measure may capture 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 they travel through as they interact with other passengers on the same bus route, transfer from bus to bus, and stop to run errands. For each person, we calculate a minimum convex polygon using the reported destinations as the corners. Figure 1 illustrates the difference between a convex and concave polygon. A convex polygon is the minimum area which encompasses all points, with no internal angle that exceeds 180 degrees.

Convex polygon Concave polygon

Figure 1

Because polygons require at least three vertices, or destinations, we have data to calculate polygons for 2,047 respondents in our data. The average polygon in our sample is 10.9 square miles in area and is made up of 4.1 destinations. We calculate two statistics summarizing the social characteristics of these polygons: (a) an area-weighted mean of the characteristics of all the census tracts partially or completely inside the respondent's polygon, and (b) the range of each characteristic using the procedure described above for nodes—we rank the census tracts partially or completely within the respondent's polygon and take the difference between the highest-ranked tract and the lowest ranked tract.

Other activity space definitions
Nodes and minimum convex polygons are only two of many ways of defining activity spaces. Other common ways of defining activity spaces include standard deviation ellipses, kernel density functions, and network path approaches. Standard deviation ellipses, perhaps the most commonly used approach, involve calculating a 2-dimensional ellipse based on the clustering of an individual's destinations in space (Newsome, Walcott et al. 1998). Ellipses drawn by calculating the distance and direction of locations from home, possibly weighting destinations by frequency or duration of time

spent. Ellipses work best with continuous or point data, for example in the case of access to healthcare service sites (Sherman, Spencer et al. 2005) or food outlets (Zenk, Schulz et al. 2011). The social characteristics data we use are discontinuous census tract polygons, which obligate us to include whole tracts in the summary measures of the area. 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 (see Figure 2), thus misrepresenting the characteristics of the population within the ellipse. It is also difficult to calculate ellipses when the number of destinations is small (Newsome, Walcott et al. 1998). For these reasons, we choose the more straightforward approach of using polygons (or nodes) comprised of the census tracts in which the locations to which respondents travel.

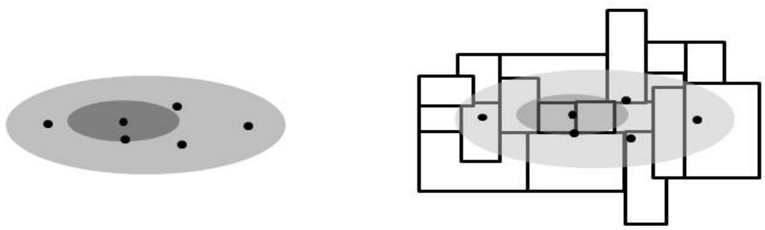


Figure 2. Ellipses with discontinuous underlying data

No consensus has been achieved about which method is best, but comparisons of results between methods have shown that the approach can be influential in the result (Sherman, Spencer et al. 2005; Kestens, Lebel et al. 2010; Zenk, Schulz 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.

ANALYTIC APPROACH

Comparing residential neighborhoods to activity spaces
In our first research question, we compare *home tracts, nodes, and polygons to one another.* We employ stacked regression models to provide an estimate of the difference between home tract, node, and polygon characteristics. We repeat these models for a total of six neighborhood measures—the proportions Latino, black, white, foreign born, and poor; and median household income.

The stacked model approach entails creating a dataset with three observations for each person: one for the home census tract characteristic, one for the node characteristic, and one for the polygon characteristic. The difference between these various neighborhood definitions for a single person is revealed by employing a random effect for person in a multilevel model.

Dependent Variables
In the analysis we use two different types of dependent variables to represent the mean and heterogeneity in the attributes characterizing home tracts and activity spaces.

<u>Area-weighed mean characteristics</u>

The first dependent variable is the *mean* value of each characteristic in individuals' home tracts and activity spaces. For the home tract, the variable is the mean across all individuals living in the tract, as reported in the 2000 U.S. Census. For activity spaces (nodes and polygons), we calculated the area-weighted mean for each characteristics based on the tracts in the nodes or polygons. We evaluate six separate characteristics of the area: proportions Latino, black, white, foreign born, and poor; and median household income.

<u>Range in characteristics</u>
The second dependent variable represents the heterogeneity of the characteristics of locations in each activity space. We measure heterogeneity as the range of a characteristic among the tracts included in the activity space. For example, if five tracts define an activity space polygon, the range in, say, the percent Latino is the highest value minus the lowest value in the space. Because, by definition, only one tract is included in home tracts, and heterogeneity is the range across tracts included in each space, we cannot define this dependent variable for home tracts.

Independent Variables
The key independent variables are the node and polygon area-weighted means (or range) on the same social characteristic. The random effect for individuals allows us to compare the home tract, node, and polygon for each person. The coefficient for these variables can be interpreted as the *difference* between the home tract and node, and home tract and polygon measure, respectively (or, in the case of range measures, the difference between the node and polygon ranges).

We also 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. For example, we hypothesize that car ownership and being employed will increase the size and diversity of activity spaces compared to home tracts.

The size of differences between home tracts and activity spaces may vary depending on respondents' own characteristics. For example, compared to the native born, foreign born individuals may be more likely to live in immigrant enclaves (i.e., home tracts with a high % foreign born) and to have activity spaces which are also immigrant enclaves, because they have less ability, opportunity, or reason to travel into other areas. We test for these types of "enclave effects" using interaction terms between individuals' characteristics and the dummy variables for node-based and polygon-based activity space.

Finally, we control for regression to the mean by the number of destinations reported and the population density of the area. In earlier models, we also included the total population of each area, but it was highly correlated with population density and the number of destinations reported because our geospatial units are measured as census tracts or groups of tracts, and tracts are constructed to be relatively homogenous with regard to population size. Also note that tract population density is correlated with tract land area because more densely populated tracts are smaller than less densely populated tracts.

Activity Space Characteristics and Individual Characteristics

To answer our second research question, we examine *differences in the characteristics of activity spaces by individual attributes*. First we investigate whether the size of activity space polygons varies by income, access to a motor vehicle, and other key individual characteristics, using OLS regression. 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 as moved in the last two years, whether the respondent has friends or family in the neighborhood and in the region, and Service Planning Area (SPA).[4] SPAs are regions of Los Angeles County.

Finally, we examine whether the characteristics of respondents are associated with their exposure to others with characteristics similar to and different from their own. In other words, are individuals in some social groups more likely to be exposed to a broad range of the population compared with people in other social groups? To test this association, we use OLS regression in which the neighborhood characteristic is the dependent variable and individual characteristics as the independent variables. 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. Again we repeat this process across twelve neighborhood outcome measures—the area-weighted mean and range in: proportions Latino, black, white, foreign born, and poor; and median household income.

The models include a random effect for home census tract to control for the clustered L.A.FANS sample design. We also control for mechanical regression to the mean by including the number of destinations reported and the population density of the area. Again, earlier models included the total population size, but this variable was dropped due to its high correlation with population density.

RESULTS

Descriptive statistics

Descriptive statistics (unweighted) for the sample and measures of neighborhood are shown in Table 1. The sample is predominantly female because the L.A.FANS' adult sample included both one randomly selected adult (RSA) per household (≥18 years old) and, in about one third of households, an additional respondent who was the mother (or primary care giver) of a randomly selected child (<18 years old). By chance, more than half of RSAs are female and virtually all of mothers or caregivers are female. The ethnic distribution, citizenship, and frequency of Spanish language use of the sample reflect 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 own a car or other motor vehicle and more than half were working at the time of the survey.

The last four rows show characteristics of respondents' activity spaces. As described above, only respondents reporting three or more points are included in the analysis. On average, the area of home tracts is considerably smaller (1.5 sq. mi.) than the area of individuals' activity spaces, whether defined in nodes (8.2 sq. mi.) or as polygons (10.9 sq. mi). The large standard errors on the land area of activity spaces show that they vary considerably among respondents.

COMPARING RESIDENTIAL NEIGHBORHOODS AND ACTIVITY SPACES

The first goal of the analysis is to determine whether residential neighborhoods adequately represent the social environments that individuals encounter on a regular basis, i.e. how similar are the characteristics of home tracts and activity spaces? In Table 2, we compare characteristics of respondents' home tracts and their activity spaces defined by nodes and by polygons. The last two columns also show the means of the same characteristics for all census tracts in Los Angeles County

[4] See http://publichealth.lacounty.gov/chs/SPAMain/ServicePlanningAreas.htm.

and in the Greater Los Angeles 5-county region.[5] In addition to the mean, Table 2 includes the range of values of the six dependent variables among the tracts that are included in activity spaces. These measures are shown in the second row of each cell in the nodes and polygons columns.

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. The average median household income in respondents' home tracts is also lower than in their activity spaces, although the difference between home tract and activity space polygons is small. Population density in home tracts is also higher than in activity spaces. These results are consistent with the fact that the most ethnically homogeneous tracts in Los Angeles are predominantly Latino – including a high proportion of lower income and foreign-born residents – or predominantly white. Because of the relative sizes of the Latino and White populations, predominantly Latino tracts are more common and they are also over-represented in the L.A.FANS sample because of the oversample of very poor and poor 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, 2.7 square miles larger than node-based activity spaces. However, it may also reflect greater correlation between home tract characteristics and those of destinations than between home tracts and areas which must be traversed to reach locations.

The multivariable models in Table 3 allow us to take account of these and other factors in comparing home tracts and activity spaces. In general, the results suggest that home tracts are significantly different from activity spaces in terms of average socioeconomic characteristics. Only in the cases of percent Latino and percent black are one of the activity space measures not highly statistically significant – and in both these cases the other activity space measure's coefficient is.

Even when we hold constant a wide range of individual characteristics, control for population density and the number of destinations reported, and include home tract level random effects (which mitigate the effects of the sample design) and individual random effects, the results in Table 3 are much the same as the bivariate results in Table 2. Specifically, compared to home tracts, in individuals' activity spaces the population is less Latino, more white, more black, less foreign born, and less likely to be poor and low income.

To test whether differences between home tracts and activity spaces vary depending on respondents' own characteristics, we estimated a set of interactions in each model between the two activity space dummies and each individual characteristic. For example, the first model -- in which the dependent variable is the proportion of the population that is Latino --includes interactions between the two activity space dummies and whether or not the respondent is Latino. All of the interaction terms are statistically significant, except for that between node and being African American, in the model predicting the percent black. For most of the models, individual characteristics match most closely with those in the home tracts and less closely with those in activity spaces. For example, Latinos' home tracts are more likely to have a higher proportion Latino than their activity spaces. However, there are exceptions. For example, for blacks, the situation is reversed. Blacks' polygon-based activity spaces are more likely to have a high proportion of black residents than their home tracts – although the differences are not large.

[5] Including the counties of Los Angeles, Ventura, San Bernardino, Kern, and Orange

In summary, we find that generally the characteristics of home tracts in Los Angeles do not represent the social environments to which adults are exposed on a regular basis – as represented by activity spaces.

DIVERSITY IN THE ACTIVITY SPACES OF INDIVIDUALS

The second goal of the analysis is to assess how frequently individuals encounter social class and race/ethnic groups other than their own, as part of their routine activities. To do so, we examine variation in activity space characteristics by respondents' attributes using both polygon- and node-based activity space definitions.

Because the size of activity spaces itself is likely to affect the diversity of social groups that individuals encounter, we first examine the determinants of activity space size by regressing activity space size on a set of individual and home tract characteristics. Table 4 shows the results of two models, the first with a set of basic characteristics and the second adding information on the whether the respondent moved recently and social contacts variables. Both models include dummies for Service Planning Areas which are regions of Los Angeles County. The largest and most significant coefficient is for Antelope Valley which is the most sparsely populated region of the County. Activity spaces are also significantly larger in the San Gabriel Valley and East Los Angeles -- both regions with a high proportion of commuters – but the coefficients are significant only in the simpler model 1.

For individual characteristics, black respondents have significantly larger activity spaces than whites and Latinos. Over the past few decades, African Americans have moved out of traditionally black neighborhoods (e.g., South LA) and into ethnically mixed neighborhoods (or in some cases, out of Los Angeles County). Despite residential mobility, many blacks have retained ties (church, employment, family, shopping) with their former neighborhoods (Sastry, Pebley et al. 2004). The larger activity spaces of black respondents are, at least partly, a reflection of this process. Higher education is significantly associated with larger activity spaces. Older people have marginally smaller activity spaces, although this relationship is significant only for model 1. Employed individuals have, not surprisingly, larger activity spaces, but this relationship is significant only in model 2. Perhaps most surprising is that vehicle ownership is not related to activity space size, but this may be because vehicle ownership is correlated with other variables in the model.

In model 2, we add variables representing social ties and relationships in the neighborhood and Southern California. These additions do not 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. This makes sense since movers may not change employers or other locations, or may do so gradually. Having friends (but not family) in the neighborhood reduces the size of activity spaces, although this effects are only marginally significant.

In Tables 5 we assess how frequently individuals encounter social class and race/ethnic groups other than their own, as part of their routine activities. Table 5 shows the results for polygon-based activity spaces. The results for node-based activity spaces, which are very similar to the polygon-based results, are shown in Appendix Table A and not discussed in detail. We estimated a separate model for each outcome. As described in the notes at the bottom of the table, all models include interactions between the number of locations that define the activity space and area population density with vehicle access and family income. The coefficients on these interactions are not shown because they are small and generally not significant.

The results in Table 5 are summarized in Figures 1a-c and 2a-c. These figures show the predicted outcome variables (percent Latino, percent white, etc.) by each individual's *own* characteristics, controlling for all other variables in each model. The predicted values of each outcome variable were calculated using the regression coefficients and the means of independent variables, shown in Tables 1 and 2, except for the independent variable under consideration which is set at a specified value. For example, to calculate the % Latino in the activity spaces of white respondents, all x-variables were set at their sample means except for the dummies for race/ethnicity. Because "white" is the omitted variable, the value of x for all the other race/ethnic dummies was set to zero for this calculation.

The results in Figure 1a examine the associations of individual race/ethnicity and the attributes of their activity spaces. Almost all of the coefficients on the race/ethnicity dummies in all models in Table 5 are statistically significant. Figure 1a shows that an individual's own race/ethnicity is strongly associated with the race/ethnic composition of his/her activity space – e.g., the activity spaces of black respondents have significantly higher proportions of blacks than those of respondents of other races/ethnicities. However, mirroring the demographic composition of Los Angeles, the largest race/ethnic group in activity spaces of any ethnic subgroup of respondents is Latino – the percent Latino is about 40% for all groups. In contrast, Latinos and blacks are exposed to a relatively small proportion of whites in their activity spaces; Latinos are also exposed to a relatively small proportion of blacks. In everyday life, Latinos live and travel in predominantly Latino areas (with an average of more than 60% Latino), whereas neither whites' nor blacks' activity spaces are composed primarily of their own race/ethnic group.

All race/ethnic groups' activity spaces include a relative high proportion of foreign born residents, but the average proportions are higher for Latinos and those in other ethnic groups. The coefficient for the black-white difference is not statistically significant, but those for both Latinos and other race/ethnic groups are significant. The percent foreign born in whites' activity spaces is significantly lower than in those of Latinos and other race/ethnic groups, but not significantly different from those of blacks. Whites' and other race/ethnicity groups' activity spaces include a lower percent poor, compared to Latinos and blacks, whose activity spaces have a significantly higher proportion poor than whites.

Figure 1b shows the predicted mean values according to respondents' socioeconomic characteristics and labor force participation, net of other individual and activity space attributes. The first variable, years of education, is statistically significant in every model in Table 5, except for the model predicting the percent black in activity spaces. Education (in years completed) is included as a continuous variables in the models. We calculate the predicted values for three educational attainment levels: 8 years, 12 years (or high school completion), and 14 years (or some college). Although most are significant the differences by educational attainment in activity space attributes in Figure 1b are not large. Compared with respondents who completed 8 years of school, those with 14 years of education have activity spaces that are slightly less Latino, more white, and slightly less poor, all else being equal.

None of the coefficients on current work or family income are statistically significant in Table 5. There predicted values are shown here in masked in gray only for comparison.

Finally, Figure 1c shows the predicted values of median household income in activity spaces, based on results shown in the next to last column in Table 5. The coefficients on the race/ethnic categories and education variable are statistically significant, but those for current work and family income are not. The activity spaces of whites and other race/ethnic groups have significantly higher median household incomes than for blacks and Latinos. Not surprisingly, respondents with more education have activity spaces with a higher median income.

Next we investigate the *range* of census tracts found in each respondents' activity space in Figures 2a-c (coefficients and significance tests are in Table 5). As a reminder, the dependent variable in these models is the difference between the highest and lowest value of the outcome variable for the tracts within each respondents' activity space. Since 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. 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 whether a respondent routinely visits *tracts* with similar or difference characteristics.

As Table 5 shows, the coefficients for individual race/ethnicity on the range of each outcome variable in Figure 2a are almost all statistically significant. Black respondents appear to have the most highly variable activity spaces of any of the race/ethnic groups. The range in proportion Latino, black, foreign born, and in poverty is larger than for whites, Latinos or the other race/ethnic group. These results may be linked to social processes in Los Angeles, described earlier, in which some African Americans have moved out of traditionally black neighborhoods in Los Angeles. Those who left may return regularly to places of worship and stores, and to visit friends and family. Some may also continue to work in historically black areas although they live in primarily non-black tracts. All of 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, except for the % white which varies more for whites' activity spaces than for those of other race/ethnic groups.

In the case of the socioeconomic variables in Figure 2b, several are statistically significantly associated with the range of characteristics in individuals' activity spaces. These include the coefficient of schooling on the range in % white, currently working in models predicting the range in % white, % Latino, and % in poverty, and family income on the range in % Latino and % white. However, Figure 2b shows that none of these associations is large.

Figure 2c shows the results for range in median household income within activity spaces. Several of the coefficients for race/ethnic groups are statistically significant, as is years of schooling. However, neither of the coefficients for current employment status nor family income is. Latinos and members of other race/ethnic groups visit places with a significantly smaller range of income than whites do. The same is true for blacks, but the coefficient is not significant. Thus, whites, on average, travel in higher income areas than other race/ethnic groups, but they also are exposed to a somewhat broader range of areas in terms of income. The results for education show that more years of schooling is associated with activity spaces that have a wider range of income levels.

DISCUSSION

Our goal in this paper is to answer two questions. First, do census tracts adequately represent the social environments in which individuals move on a routine basis? In general, the answer to this question is no. The characteristics of activity spaces, as defined in this paper, are significantly different from the characteristics of respondents' home census tracts. Specifically, in Los Angeles, activity spaces have a lower % Latino and white, higher % black, lower % foreign born, lower % in poverty, and higher median family income compared with home 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 have attempted to control for this effect by including the number of destinations reported and the population density of the area in the models in Table 3. Nonetheless, whether regression to the mean plays a significant role in the differences or not, the reality is that individuals' activity spaces are often quite different than home tracts. 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. Consistent with a handful of previous studies (Sastry, Pebley et al. 2004; Inagami, Cohen et al. 2007; Crowder and South 2011; Matthews 2011), our results sugges that researchers interested in the effects of individuals' social environments on behavior and well-being should consider areas outside home neighborhoods. Many people spend the majority of their 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? One conclusion is that individuals' own characteristics are closely associated with those of their activity spaces, e.g., whites' activity spaces have a higher proportion of whites, blacks' activity spaces have a higher proportion of blacks, etc. The activity spaces of respondents with more years of schooling include a lower % in poverty and foreign born, and have a higher median income than activity spaces of other respondents. The results also show that most activity spaces have a high % Latino, reflecting the demographic composition of Los Angeles County.

The results for ranges suggest that whites have the least diverse activity spaces (except for median family income) and that blacks have the most diverse activity spaces. Both Latinos and blacks are in activity spaces with relatively low proportions white (Figure 1a) but especially for blacks the range of % white in their activity spaces is quite broad and almost the same as the range for white respondents (Figure 2a). Blacks also have the greatest range in the % Latino, % black, % foreign born, and % poor in their activity spaces. The range of median household income in the activity spaces of black respondents is exceeded only by the range for whites. More educated respondents are also exposed to activity spaces with higher median income and a wider range of median income.

Latinos live and travel around in heavily Latino, foreign born, and poor neighborhoods. The range in ethnicity, nativity status and poverty in activity space characteristics is higher for Latinos than for whites, but less than that for blacks.

In summary, these results suggest that blacks are the least socially isolated group in Los Angeles, although on average, their activity spaces contain a relatively low proportion of whites. They tend to move among tracts with highly variable race/ethnic composition and socioeconomic status. Whites are, in many senses, on the other end of the scale, having the lowest ranges in activity space characteristics and being far more likely than any other group to have activity spaces with a sizeable proportion of whites. Latinos are also isolated in a way because their activity spaces have very high proportions Latino and foreign born, and relatively low variability in these measures.

Table 1. Descriptive Statistics for the Sample (n=2,041, Unweighted)

	% or Mean (SD)
Female gender	75%
Education (years)	12.5 (4.4)
Number of children in household	1.7 (1.4)
Race/Ethnicity	
Latino	53%
White	28
Black	11
Asian	7
Pacific Islander	0
Native American	1
Other	0
US Citizen	66%
Spanish-language interview	36%
Has a vehicle	79%
Moved in the last 2 years	27%
Currently working	64%
Age (years)	39.9 (13.3)
Family Income ($1,000)	56.8 (98.6)
Number of destinations reported	4.1 (0.9)
Area of home tracts (sq. mi.)	1.5 (9.2)
Area of activity space nodes (sq. mi.)	8.2 (36.7)
Area of activity space polygons (sq. mi.)	10.9 (34.3)

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)	**5-county area Tracts** Mean (SD)
Observations	2041 adults	2041 adults	2041 adults	2055 tracts	3207 tracts
Area (sq mi)	1.5 (9.2)	8.2 (36.7)	10.9 (34.3)	2.0 (13.4) Total area: 4,102 square miles	10.9 (162.7) Total area: 35,049 square miles
Population density (ppl/sq mi, 1000's)	14.7 (11.0)	10.1 (7.5)	10.2 (6.8)	12.5 (10.9)	10.1 (9.8)
Population	5,408 (2,114)	20,180 (6,821)	168,077 (262,898)	4,633 (1,782) Total population: 9,519,962	4833 (2254) Total population: 15,499,319
% Latino	53.4 (30)	46.9 (26.3) 34.4 (22.9)	48.7 (25.3) 55.6 (28.2)	43.5 (29.6)	39.7 (28.8)
% White	25.3 (26.2)	29.8 (24.0) 27.3 (22.6)	26.6 (22.5) 43.3 (28.0)	32.0 (28.5)	39.1 (29.4)
% Black	8.2 (10.5)	8.6 (11.0) 12.7 (15.9)	9.5 (11.6) 26.0 (26.3)	9.2 (15.6)	7.0 (13.1)
% Foreign born	39.5 (15.3)	36.2 (13.0) 21.0 (13.1)	37.5 (12.3) 37.3 (19.4)	35.5 (16.4)	30.6 (17.1)
% Poverty	22.1 (14.1)	19.2 (11.5) 17.6 (12.4)	20.0 (11.0) 34.3 (21.4)	17.9 (13.0)	15.7 (12.4)
Median hh income ($1,000)	41.8 (23.4)	44.9 (20.7) 27.2 (25.3)	42.9 (18.0) 55.2 (42.6)	46.5 (25.0)	49.1 (25.4)

Table 3: Stacked Regression Models Comparing the *Average* Characteristics of Home Tracts, Nodes, and Polygons

	% Latino	% White	% Black	% Foreign Born	% Poverty	Median Household Income ($1,000)
Nodes Indicator	-0.0303[c]	0.0616[c]	0.0034	-0.0471[c]	-0.2111[c]	28.0350[c]
Polygon Indicator	-0.0018	0.0369[c]	0.0109[c]	-0.0323[c]	-0.2253[c]	39.5802[c]
Population density of area (1,000s)	0.0065[c]	-0.0067[c]	0.0010[b]	0.0101[c]	0.0072[c]	-0.9401[c]
# Destinations reported	-0.0074	-0.0009	0.0055[a]	-0.0047[a]	-0.0042[a]	0.2241
Female	-0.016	0.0143	-0.0091	-0.0046	-0.0122[b]	0.7877
Age (years)	-0.0002	0.0001	-0.0002	-0.0006[c]	-0.0007[c]	0.1167[c]
Number of children in household	0.003	-0.0042	0.0055[c]	-0.0024	0.0026[a]	-0.1822
Education (years)	-0.0128[c]	0.0107[c]	-0.0015[a]	-0.0039[c]	-0.0050[c]	0.8844[c]
Family income (logged)	-0.0321[c]	0.0355[c]	-0.0084[c]	-0.0095[c]	-0.0262[c]	5.8431[c]
Currently working	0.0071	-0.0112	-0.0015	0.0048	-0.0011	-1.1018
Household has a personal vehicle	-0.0157	0.0094	-0.0041	-0.0114[a]	-0.0275 [c]	0.5598
Latino	0.2921[c]		0.0021	0.0690[c]	0.0470[c]	-8.9823[c]
White		0.2732[c]				
Black	0.1448[c]	-0.0241[a]	0.1329[c]	0.0067	0.0751[c]	-13.4919[c]
Other race/ethnicity	0.0687[c]	0.0640[c]	0.0188[a]	0.0431 [c]	0.0071	-5.9062[c]
Polygon x Latino	-0.0836[c]					
Node x Latino	-0.0648[c]					
Polygon x white		-0.0871[c]				
Node x white		-0.0604[c]				
Polygon x black			0.0180[b]			
Node x black			0.0039			
Polygon x citizen				0.0190[c]		
Node x citizen				0.0212[c]		
Polygon x log family income					0.0198[c]	-3.7288[c]
Node x log family income					0.0176[c]	-2.4174[c]
Constant	0.8340[c]	-0.2628[c]	0.1488[c]	0.4542[c]	0.5179[c]	-18.8585[c]
sigma_e	2.1163	2.1004	2.0585	2.0691	2.0622	211.5939
Rho	0.652	0.651	0.657	0.501	0.483	0.445
N	6123	6123	6123	5952	6123	6123
Clusters	2041	2041	2041	2041	2041	2041

[a]$p<0.05$ [b]$p<0.01$ [c]$p<0.001$

Table 4. Size of Activity Space (Square Miles) As a Function of Individual Characteristics

	(1)	(2)
	b	b
Female	-3.5400[a]	-3.5420
Education (years)	0.5513[a]	0.5567[a]
Latino	-1.2138	0.0103
Black	9.5265[b]	9.5350[b]
Other race/ethnicity	2.6152	5.8451
Age (years)	-0.1426[a]	-0.0818
Family income (logged)	0.7344	1.1632
Currently working	3.1699	4.3269[a]
Household has a personal vehicle	0.5997	1.7156
Number of children in hhld	-0.6371	-0.7411
SPA 1: Antelope Valley	61.5712[c]	70.5336[c]
SPA 2: San Fernando Valley	2.8300	2.0484
SPA 3: San Gabriel Valley	5.9585[a]	5.8055
SPA 5: West	-2.9475	-3.7487
SPA 6: South	1.4909	1.1014
SPA 7: East	6.2983[a]	5.4160
SPA 8: South Bay	4.7589	3.5022
Moved in last 2 years		5.9996[b]
Any family in the neighborhood (yes/no)		-0.0450
Any friends in the neighborhood (yes/no)		-4.2000[a]
Any family in Southern California (yes/no)		-0.1819
Constant	-1.3888	-9.0797
R-sqr-adjusted	0.08	0.1
N	2041	1629

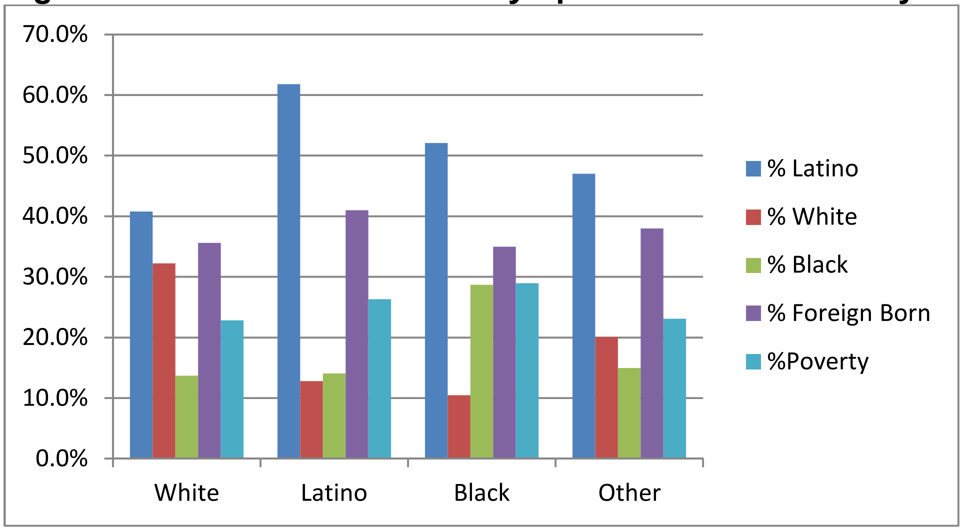
[a]p<0.05 [b]p<0.01 [c]p<0.001

Table 5. Average and Range in Polygon Characteristics as a Function of Individual Characteristics

	% Latino		% White		% Black		% Foreign Born		% Poverty		Median Household Income ($1,000)	
	mean	range	mean	range	mean	range	mean	range	mean	range	mean	range
Education (years)	-0.0108[c]	-0.0003	0.0087[c]	0.0054[c]	-0.0014[a]	-0.0004	-0.0023[c]	0.0018	-0.0042[c]	-0.0007	0.7974[c]	1.2782[c]
Family income (logged)	-0.0223	-0.0637[a]	0.0282	-0.0640[a]	0.0009	0.0182	-0.0012	0.0004	-0.0131	-0.0029	2.3353	-3.9247
Currently working	0.0021	0.0416[b]	-0.0088	0.0290[a]	-0.0029	0.0131	0.0077	0.0186[a]	-0.0039	0.0232[a]	0.0063	2.7394
Latino	0.2103[c]	0.0814[c]	-0.1943[c]	-0.0604[c]	0.0035	0.0395[a]	0.0536[c]	0.0437[c]	0.0348[c]	0.0772[c]	-5.5025[c]	-8.4989[c]
Black	0.1131[c]	0.1776[c]	-0.2176[c]	-0.0113	0.1499[c]	0.2930[c]	-0.0067	0.0888[c]	0.0608[c]	0.1648[c]	-8.3134[c]	-4.2172
Other race/ethnicity	0.0623[c]	0.0978[c]	-0.1210[c]	0.0041	0.0127	0.0288	0.0235[b]	0.0463[b]	0.0022	0.0550[b]	-2.6658[a]	-7.1791[a]
Population density (1,000's)	0.0055[c]	-0.0056[c]	-0.0057[c]	-0.0090[c]	0.001	-0.0007	0.0088[c]	-0.0060[c]	0.0077[c]	-0.0044[c]	-0.8415[c]	-1.7130[c]
# Destinations reported	-0.0449	-0.0604	0.0435	-0.1146	0.0329	0.1230[a]	0.003	0.0629	-0.012	0.0622	0.4421	-7.0301
Female	-0.012	-0.0271	0.0131	0.0028	-0.0134[a]	-0.0366[b]	0.0003	-0.0179	-0.0095[a]	-0.0234[a]	0.4774	-1.0394
Age (years)	0	-0.0007	0	-0.0007	-0.0002	-0.0003	-0.0005[b]	-0.0006	-0.0006[c]	-0.0007	0.0597[a]	-0.0558
Number of children in household	0.0051	-0.0139[b]	-0.0060[a]	-0.0175[c]	0.0048[b]	-0.0022	-0.0007	-0.0074[a]	0.0035[b]	-0.006	-0.3652	-2.4059[c]
Household has a personal vehicle	-0.1581[b]	0.0508	0.1604[c]	0.1057	-0.0287	-0.1136	-0.0612[a]	0.0212	-0.0536[b]	-0.0882	9.7876[a]	6.1519
Constant	0.7835[c]	0.8503[b]	-0.0128	0.8399[c]	0.06	-0.141	0.3573c	0.1343	0.3517[c]	0.1674	14.5714	66.8101
R-sqr-adjusted	0.46	0.16	0.49	0.25	0.18	0.18	0.55	0.16	0.59	0.15	0.46	0.29
N	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041

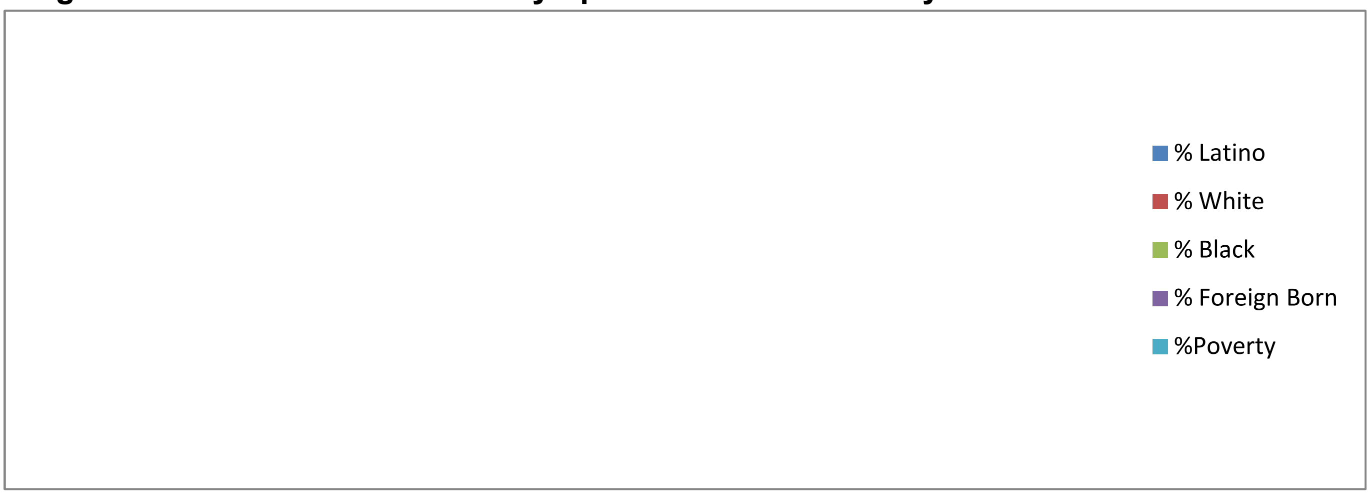
[a]p<0.05 [b]p<0.01 [c]p<0.001 Notes: Models including a fixed effect for home census tract do not change the results. There is no substantive difference between models including pop density, total pop, obs_count alone and all three together. The models in the table include interactions between: (a) number of destinations and vehicle access, number of destinations and family income, population density and vehicle access, and population density and family income.

Figure 1a. Predicted *Mean* Activity Space Characteristics by Individual Race/Ethnicity.



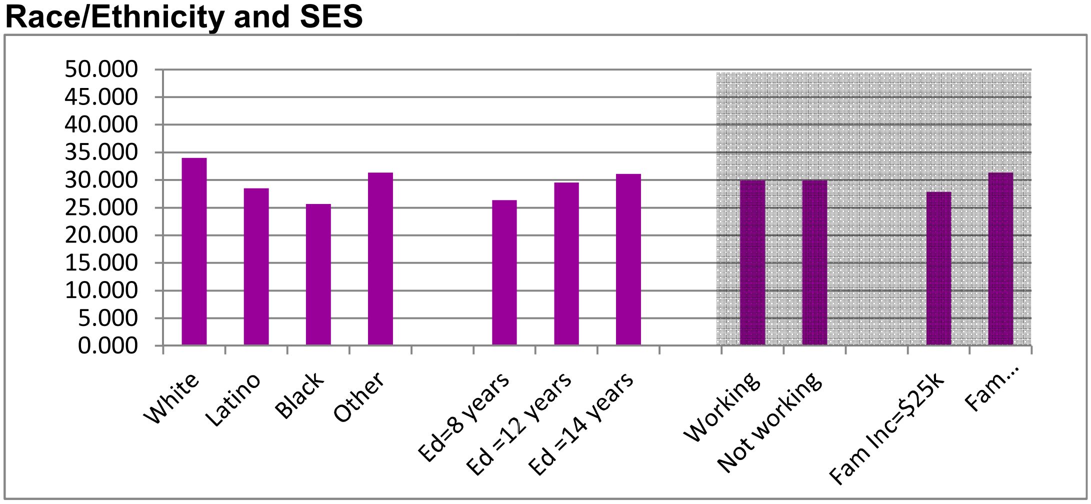
Note: Activity spaces defined by polygons. Derived from Table 5.

Figure 1b. Predicted *Mean* Activity Space Characteristics by Individual SES



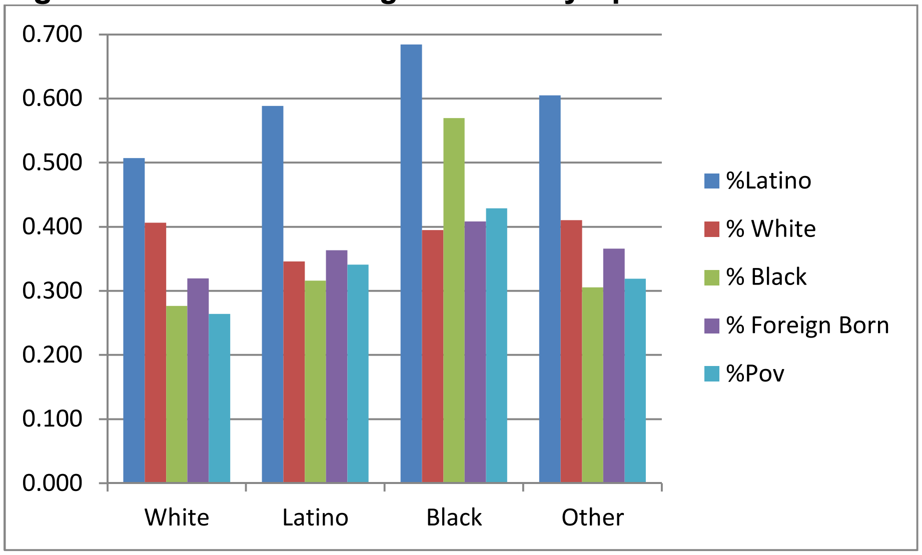
Note: Activity spaces defined by polygons. Derived from Table 5.

Figure 1c. Predicted *Mean* Activity Space Median Household Income by Individual Race/Ethnicity and SES



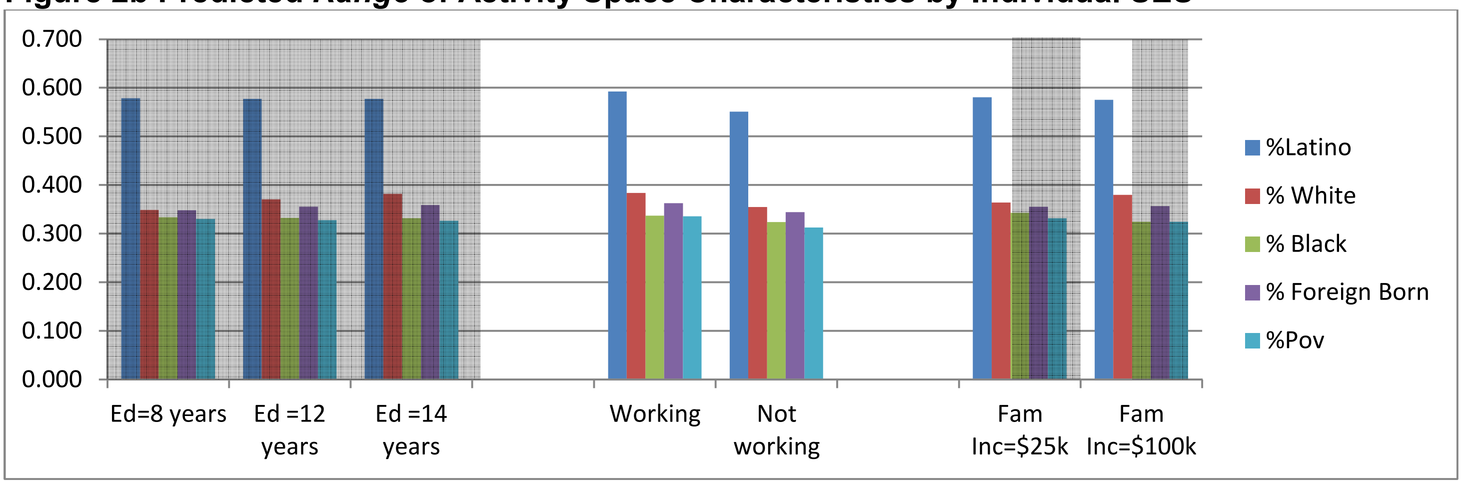
Note: Activity spaces defined by polygons. Derived from Table 5.

Figure 2a. Predicted *Range* of Activity Space Characteristics by Individual Race/Ethnicity



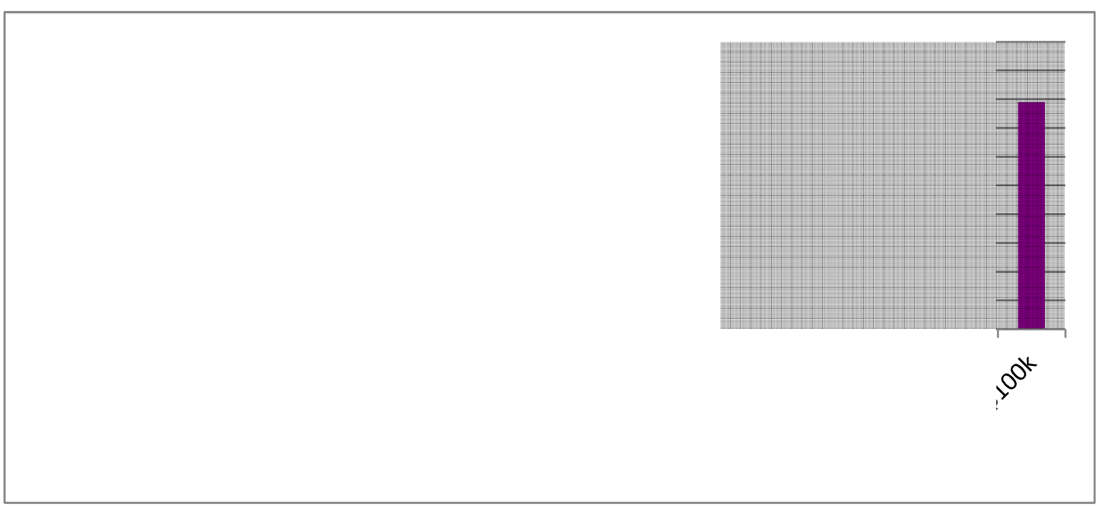
Note: Activity spaces defined by polygons. Derived from Table 5.

Figure 2b Predicted *Range* of Activity Space Characteristics by Individual SES



Note: Activity spaces defined by polygons. Derived from Table 5.

Figure 2c. . Predicted *Range* of Activity Space Median Household Income by Individual Race/Ethnicity and SES



Note: Activity spaces defined by polygons. Derived from Table 5.

Appendix Table A. Average and Range in Node Characteristics as a Function Of Individual Characteristics

	% Latino		% White		% Black		% Foreign Born		% Poverty		Median Household Income ($1,000)	
	mean	range	mean	range	mean	range	mean	range	mean	range	mean	range
Education (years)	-0.0122[c]	0.001	0.0098[c]	0.0053[c]	-0.0009	-0.0008	-0.0030[c]	0.0009	-0.0040[c]	0.0004	0.8188[c]	0.7482[c]
Family income (logged)	-0.0201	-0.0107	0.0329	-0.036	-0.0019	0.0073	-0.0114	0.0002	-0.0270[b]	-0.0026	3.6681[a]	-0.9691
Currently working	0.0019	0.0340[b]	-0.0045	0.0257[a]	-0.0048	0.008	0.0045	0.0078	0.0019	0.0127[a]	-0.8714	0.3723
Latino	0.2160[c]	0.0799[c]	-0.2091[c]	-0.0363[b]	0.0074	0.0223[a]	0.0531[c]	0.0092	0.0385[c]	0.0441[c]	-7.4745[c]	-5.2665[c]
Black	0.1098[c]	0.1398[c]	-0.2279[c]	-0.0021	0.1392[c]	0.1961[c]	-0.0001	0.0433[c]	0.0662[c]	0.0689[c]	-13.2478[c]	-5.5062[b]
Other race/ethnicity	0.0499[b]	0.0758[c]	-0.1528[c]	-0.005	0.0230[b]	0.0263[a]	0.0309[c]	0.0156	-0.001	0.0152	-4.3294[b]	-5.4257[b]
Population density of nodes (1,000's)	0.0040[c]	-0.0032[b]	-0.0041c	-0.0032[b]	0.0009	-0.0003	0.0080c	-0.0035c	0.0056[c]	-0.0034[c]	-0.6918[c]	-0.6862[c]
# destinations reported	-0.0451	0.0896	0.0444	-0.0328	0.0354	0.0780[a]	-0.0302	0.0503	-0.0418[a]	0.0275	1.0505	-7.1872
Female	-0.0071	-0.0068	0.0087	0.0113	-0.0065	-0.0082	-0.0019	-0.0111	-0.0084	-0.0039	0.8134	1.0033
Age (years)	0.0001	0.0001	-0.0002	0	-0.0001	0.0002	-0.0004[a]	-0.0006[a]	-0.0004[a]	-0.0004	0.1098[c]	0.0551
Number of children in hhld	0.0073[a]	-0.0096[b]	-0.0077[b]	-0.0131[c]	0.0064[c]	0.0055[a]	-0.0032[a]	-0.0027	0.0012	-0.0018	-0.2361	-0.7943[a]
Household has a personal vehicle	-0.1541[b]	0.0285	0.1457[b]	0.0671	0.0177	0.006	-0.0725[b]	0.0197	-0.0520[a]	-0.1159[c]	6.1166	-5.0076
Constant	0.7882[c]	0.1308	-0.0544	0.3652	0.0553	-0.0924	0.4824[c]	0.1037	0.5019[c]	0.1756	2.748	26.7376
R-sqr-adjusted	0.47	0.12	0.5	0.18	0.19	0.17	0.51	0.12	0.48	0.09	0.43	0.24
N	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041	2041

[a]p<0.05 [b]p<0.01 [c]p<0.001. Notes: Models including a fixed effect for home census tract do not change the results. There is no substantive difference between models including pop density, total pop, obs_count alone and all three together. The models in the table include interactions between: (a) number of destinations and vehicle access, number of destinations and family income, population density and vehicle access, and population density and family income.

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