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Urban Spatial Structure and the Potential for Vehicle Miles Traveled Reduction

April 2016

A Research Report from the National Center for
Sustainable Transportation

Marlon G. Boarnet, University of Southern California
Xize Wang, University of Southern California



National Center
for Sustainable
Transportation



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A National Center for Sustainable Transportation Research Report

April 2016

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Abstract

This research informs metropolitan land use planning by studying a heretofore understudied variation of land use – travel behavior interactions: how access to jobs in employment sub-centers influences household vehicle miles traveled (VMT) in the five-county Los Angeles Combined Statistical Area (CSA). We used data from 2009 National Employment Time Series to identify employment sub-centers and data from the 2012 California Household Travel Survey to measure household VMT. We then modified a standard land use – travel behavior regression to include, as explanatory variables, measures of access to jobs that are in and not in employment sub-centers. Our results shows: (1) Accessibility to jobs outside employment sub-centers often has a larger impact on VMT than the accessibility to jobs inside the sub-centers. (2) The effect of accessibility on household VMT varies in core counties and periphery counties. (3) Accessibility to jobs within 5 miles from a household’s residence has a larger association with household VMT than accessibility to jobs beyond 5 miles from the residence. (4) Moving a representative household from the centroid of Moreno Valley in Riverside County to the centroid of Koreatown in Los Angeles is associated to a 46.6 percent reduction for household-level VMT.

Introduction

Research Subject

This research informs metropolitan land use planning by studying a heretofore-understudied variation of land use – travel behavior interactions. The large literature on land use and travel behavior has documented that the association between employment access and vehicle miles traveled (VMT) has one of the largest magnitudes among land use variables (see, e.g., Ewing and Cervero, 2010, or Salon et. al., 2012). Yet the employment access variables in the research literature have not differentiated between whether drivers have access to dispersed jobs or jobs that are clustered in an employment sub-center. Clustering jobs in employment sub-centers can alter the economic geography of a region in ways that could affect trip generation and trip chaining.

Research Problem

California metropolitan areas have highly sub-centered employment patterns, and the State has emphasized policy approaches that link land use to vehicle travel (e.g. Senate Bill 375.) California’s policy makers currently have to use a literature that does not distinguish how access to employment sub-centers might influence VMT differently from access to jobs that are not in sub-centers. This is a policy shortcoming given California’s highly polycentric metropolitan structure. We help close that gap by studying how access to jobs in employment sub-centers influences household VMT.

Research Objectives

We examine whether all jobs matter equally for travel behavior, and whether access to sub-centered jobs is or is not different (in terms of the association with household VMT) from access to jobs that are not in employment sub-centers. Our study area is the five-county Los Angeles Combined Statistical Area (CSA) – Los Angeles, Orange, Riverside, San Bernardino, and Ventura Counties. Our research has three primary steps. First, we used detailed data on employment from the National Employment Time Series (NETS), matched to geocoded firm locations, to identify employment sub-centers in the Los Angeles CSA. Second, we use the most recent travel diary survey for the region, the 2012 California Household Travel Survey (CHTS), to measure household VMT, again matching the household's residence to their geocoded location. Third, we modify a standard land use – travel behavior regression to include, as explanatory variables, measures of access to jobs that are in and not in employment sub-centers.

Findings and Research Significance

Our results show the following. (1) Accessibility to jobs outside employment sub-centers often has a larger impact on VMT than accessibility to jobs inside the sub-centers. (2) The effect of accessibility on household VMT varies in core counties (Los Angeles and Orange) and periphery counties (the balance of the CSA.) (3) Accessibility to jobs within 5 miles from a household's residence has a larger association with household VMT than accessibility to jobs beyond 5 miles from the residence. (4) Moving a representative household from the centroid of Moreno Valley in Riverside County to the centroid of Koreatown in Los Angeles is associated to a 46.6 percent reduction for household-level VMT. Moves between locations with less stark differences in urban form would be associated with a smaller, but still meaningful, change in VMT. For example, a simulated move from the centroid of Moreno Valley to the centroid of Anaheim is associated with a 14 percent reduction in household VMT.

Background and Literature Review

Research Literature

There is a large literature on land use and travel behavior. For recent reviews, see, e.g., Boarnet (2011), Ewing and Cervero (2010), and Salon et al. (2012). Relatedly, the California Air Resources Board (ARB) has published policy briefs that summarize the evidence on a range of policies and programs that relate to household VMT.¹ Those briefs provide some of the basis for the literature review in Salon et al. (2012).

The literature summarizes the relationship between land use variables and household travel in the form of elasticities. An elasticity quantifies the percentage change in a dependent variable (or response variable, in this case household VMT) that is associated with a given percentage change in an independent variable (or policy variable in this case, measures of access to jobs from a household's residential location.) An elasticity greater than one implies that a given percentage change in the policy variable will lead to a larger percentage change in the response variable, and an elasticity less than one implies that a given percentage change in a policy

¹ See <http://arb.ca.gov/cc/sb375/policies/policies.htm>, accessed November 27, 2015.

variable will result in a smaller percentage change in the response variable. As an example, an elasticity of 0.25 would imply that doubling the policy variable will lead to a 25% percent increase in the response variable, while an elasticity of -0.8 would, equivalently, imply that a 50% increase in the policy variable will lead to a 40% decrease in the response variable.

The land use – travel behavior literature that is based on household travel data, now approximately three decades old, has focused on questions of causality. Are relationships between policy and response variables (or between land use and travel variables) causal associations, or do those associations reflect omitted variables that lead travelers to live in land use settings that support their desired travel patterns. See Boarnet and Sarmiento (1998) or Handy, Cao, and Mokhtarian (2006) for some examples and discussion. The evidence suggests that the association is mostly a causal one (Cao, Mokhtarian, and Handy 2009). Another line of scholarly inquiry has argued that even if the relationship between land use and travel behavior is mediated, in part, by household residential location, the policy relevance of land use might include residential location choices (see the discussion and debate in Naess (2014b), the comment by Van Wee and Boarnet (2014) and the response to the comment by (Naess 2014a)).

While questions of causality are important, we note that several other questions have been comparatively overlooked (at least until recently), and we articulate that our place in the policy literature is to focus on potential differences in employment access across sub-centered and non-centered jobs. Questions of magnitude are as important for policy as questions of causality, and the recent literature in this area has begun to consistently convert associations into elasticities to compare magnitudes. Two results from that literature are emerging. First, the elasticities of household VMT with respect to land use – travel behavior variables are in consistent ranges, with access to employment among the larger magnitudes when compared with the effect of other land use variables. The elasticity of household VMT with respect to a gravity measure of employment access is typically in the range of -0.2 to -0.3 (see, e.g., Ewing and Cervero (2010); Salon et al. (2012)). Second, using an extensive set of household demographic characteristics may help control for omitted factors related to residential selection that could bias the estimate of land use – travel behavior associations (see, e.g., Brownstone (2008)). We follow a long line of land use – travel research by examining the association between employment access and household VMT, without using adjustments for residential selection other than household demographic variables (which, per Brownstone, 2007, may be sufficient), and we innovate by examining how the elasticity of household VMT with respect to employment access varies by access to jobs in sub-center versus jobs not in sub-centers.

California's Policy Context

California's transportation policy context increasingly requires evidence about the link between land use and VMT. Senate Bill (SB) 375, passed into law in 2008, requires Metropolitan Planning Organizations to document that the combination of their Regional Transportation Plan/Sustainable Communities Strategy and the Regional Housing Needs Assessment will lead to compliance with state mandated greenhouse gas (GHG) emission reduction goals for the ground transportation sector. The Los Angeles metropolitan area is in the midst of what is likely the most ambitious rail transit construction program in the country, with six new rail transit lines opened or scheduled to open during this decade. The land use and transportation plans of

the Los Angeles metropolitan area are increasingly tied to understanding and leveraging the relationship between land use and travel behavior. The same holds for other metropolitan areas in California, which are following largely similar policies that promote transit-oriented development and alternatives to automobile travel. Within that context, access from a household's residence to job locations throughout a metropolitan area is typically among the stronger predictors of household VMT.

Measuring Access to Employment

Employment access is measured by a gravity variable, typically of the form shown below.

$$access_i = \sum_{j \neq i} \frac{E_j}{D_{ij}^\alpha} \quad (1)$$

Where access = gravity measure of job access from location "i"

E = employment in geographic units, "j"

D = distance between locations (or geographic units) "i" and "j"

α = an exponent for the distance relationship

and there are "n" locations or geographic areas in the study region, with the summation implicitly over all geographic units within the region.

Equation (1) will yield an access measure, the distance-weighted sum of jobs, for each region within the study area. The key element of the gravity access formulation is that, from any location (e.g. a household's residence, "i"), jobs are summed with a weight that is the inverse of the distance between the household location and the jobs. The more distant jobs are, the less they matter. This is the classic gravity formulation for access, so named because in early formulations, with interacted measures of employment and population and origins and destinations of trips, the mathematical formula was similar to the formula for gravitational potential energy (see, e.g., Haynes and Fotheringham (1984)). The exponent on distance, α , expresses how access dampens with distance. In recent studies of land use and travel the exponent is equal to two, giving a dampening effect that is a quadratic function of distance.

Note that employment (or job) access proxies a broad range of trip destinations, not just work locations. Trip destinations are in very large part places where there are jobs, whether the trip is for work, education, entertainment, shopping, or services. Hence the employment access variable measures access to opportunities that should predict all travel, not just work-based (or commute) travel.

Identifying Sub-Centers

Employment sub-centers have been identified since the pioneering work of McDonald and McMillen (1990) and Giuliano and Small (1991). The early methods for identifying sub-centers divided a metropolitan area into geographic units (such as census tracts), and contiguous places with high employment densities were then aggregated, calling such an aggregation a sub-center

if total employment and employment density were both above a threshold. Two thresholds are key – the cutpoint for high employment density and the minimum level of total employment necessary to be classified as an employment sub-center. This approach has often settled at or near what is called a “10-10” criterion, identifying geographic areas with employment density above 10 jobs per acre as “high density” and hence candidate components of a sub-center, and then requiring that the full sub-center have more than 10,000 jobs. Some approaches use non-parametric methods to identify employment sub-centers (e.g. Redfearn (2007)), although for this research we use the more straightforward parametric approach, described in the methods section. There has been a large amount of research on sub-centers in the Los Angeles metropolitan area and the approach that we use in this research (described later) conforms well to approaches used by policy agencies (including the Southern California Association of Governments).

Methods and Data

Employment Sub-centers in the Los Angeles Combined Statistical Area

Identifying Employment Sub-centers in the Los Angeles CSA

This study defines the Los Angeles Region as the Los Angeles Combined Statistical Area (CSA). The Los Angeles CSA consists of five counties: Los Angeles, Orange, Ventura, San Bernardino and Riverside (Figure 1). This five-county area has 17,877,006 people, 48% of the total population in the state of California. The area has 176 incorporated cities. The employment data of the Los Angeles CSA comes from the 2009 National Establishment Time-Series (NETS) Database, a proprietary dataset developed by Dun and Bradstreet. The 2009 data are the most recent year available to the research team due to the nature of previous licensing agreements within METTRANS for the NETS data. We believe that the spatial pattern of employment sub-centers is likely stable over time, and that comparing 2012 travel (as is described later) to 2009 patterns of employment is appropriate for the purposes of this study. The NETS database includes the geographic location (longitude and latitude) and the employment size of each business establishment in the region. For a more detailed description about the NETS database, see Walls and Associates (2008).



Figure 1 Study area: Los Angeles CSA

We identified employment sub-centers of Los Angeles CSA using the 2009 NETS database by the “95% - 10k” method introduced by Giuliano et al. (2015). We first divided the Los Angeles CSA into 34,527 hexagons, such that each hexagon has an area of 640 acres or one square mile. The employment centers contain hexagons with employment density larger than the 95 percentile of the entire region, or 1,115 jobs per square mile. Contiguous hexagons with employment densities above the region’s 95th percentile are grouped together into candidate sub-centers. When those contiguous collections of high density sub-centers have a total of at least 10,000 jobs, the location is identified as an employment sub-center. Using this “95% - 10k” method we identified 46 employment centers in the Los Angeles CSA, which will be discussed in detail in the next section. For a more detailed discussion on the “95% - 10k” method in determining the employment centers, see Giuliano et al. (2015).

Distribution of Employment Sub-centers in the Los Angeles Region

By applying the “95% - 10k” method introduced by Giuliano et al. (2015), we identified 46 employment sub-centers in the Los Angeles (Figure 1). The 46 employment sub-centers contain 3,331,205 total jobs, 39.8% of the total 8,366,369 jobs in the Los Angeles CSA. Compared to a similar study using the 1980 Census Journey-to-Work data by Giuliano and Small (1991), employment is more concentrated in the employment sub-centers in 2009 than in 1980. In the

1980 study, Giuliano and Small (1991) identified 32 employment sub-centers in the same region, containing 32.1% of the region's total employment.

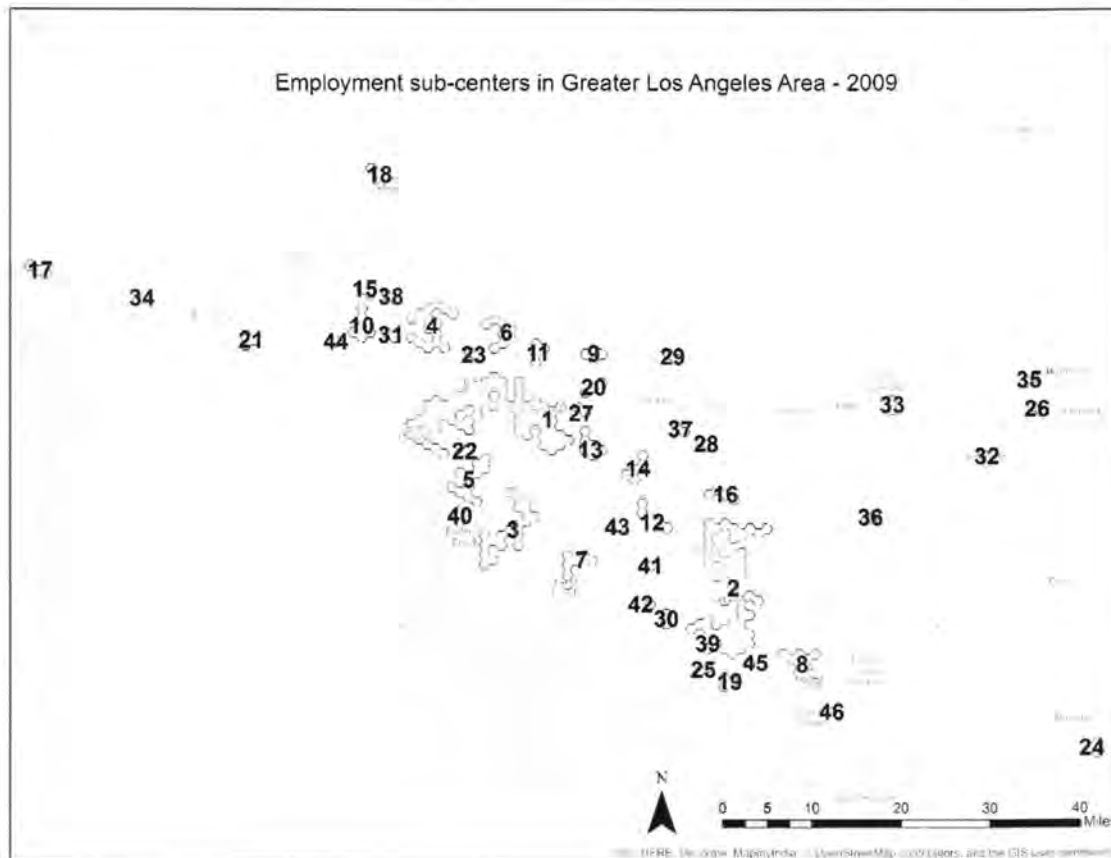


Figure 2 Employment sub-centers in Los Angeles CSA

The largest employment sub-center in the Los Angeles CSA is a corridor extending from downtown Los Angeles westbound to Santa Monica through the Wilshire corridor. This sub-center contains 1,107,139 total jobs, 33.2% of the total jobs located inside all employment sub-centers and 13.2% of the total jobs in Los Angeles CSA. The second largest employment sub-center is in the heart of Orange County, extending from Anaheim to Irvine through Santa Ana. This employment sub-center has 605,284 jobs, 18.2% of the total jobs located inside the employment sub-centers and 7.2% of the total jobs in Los Angeles CSA. The third, fourth and fifth largest employment sub-centers are located in the South Bay, San Fernando Valley and Los Angeles International Airport (LAX) areas, respectively.

Figure 2 also shows that 37 of the 46 employment sub-centers in Los Angeles CSA are located in the two most urbanized counties – Los Angeles and Orange. There are three employment sub-centers located inside each of the three other suburban or exurban counties: Riverside, San Bernardino and Ventura.

Household VMT

The household VMT data are from the 2012 California Household Travel Survey conducted by the California Department of Transportation. The CHTS used an activity diary that captured information about trips. Each household member was asked to estimate trip length for every trip during his or her diary day. We used those data to calculate VMT for households, aggregate trip length for all trips made in household vehicles, taking care not to double-count VMT for trips in vehicles with multiple household members. Trips in vehicles not owned by the household are also counted in the sum of household VMT. In the five-county Los Angeles CSA, 14,877 households were surveyed in the CHTS. We considered households with a VMT higher than 200 on the survey day to be outliers and removed them. The average daily household VMT in our sample is 35.83 and the standard deviation is 40.97. As Figure 3 indicates, more than 25% of the households have zero VMT in the survey day. Such a distribution indicates that our sample is left-censored and using an ordinary least squares (OLS) model is not appropriate. We use Tobit regression in our analysis (described later). Figure 4 shows the spatial distribution of the household VMT in our sample.

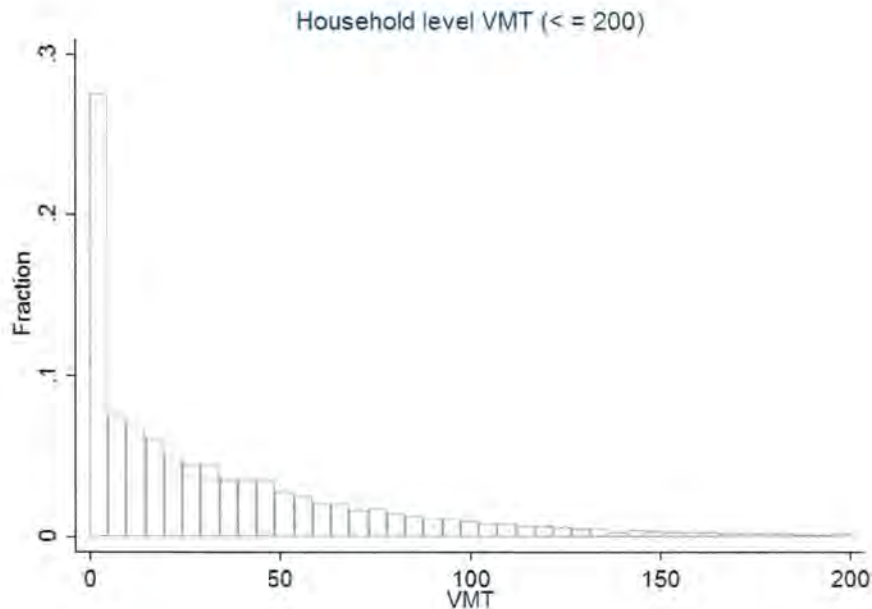


Figure 3 Distribution of Household VMT (less than 200) of the sample

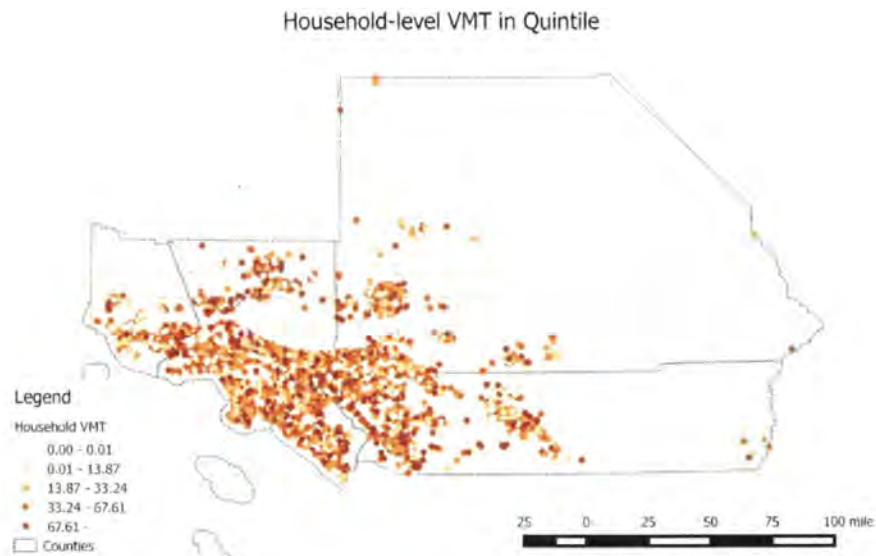


Figure 4 Spatial distribution of VMT of the households in Los Angeles MSA

Measuring Access to Jobs In and Outside of Employment Sub-centers

We created a gravity-type job accessibility index to measure the impact of the employment sub-centers on individual household VMT. Mathematically, the value of the job accessibility index is dependent on two factors: the number of jobs in the region and the distance from the jobs to a resident's hexagon. The job accessibility index is defined as the number of jobs accessible damped by the distance between the jobs and the residence. We use hexagons as the unit of analysis to create the accessibility variable, as shown below.

$$emp_acc_i = \left(\sum_{j \neq i} \frac{E_j}{D_{ij}^x} + \frac{E_i}{D_0^x} \right) \cdot \frac{1}{10,000}$$

Where: emp_acc_i = the job accessibility index of hexagon i ;

x = damping factor, which is equal to 2 (quadratic damping)

E_j = number of jobs inside hexagon j ;

D_{ij} = distance (in miles) between centroids of hexagon i and hexagon j ;

E_i = number of jobs inside hexagon i ;

$D_0 = 1$ mile, in other words, we assume that jobs within a hexagon all locate 1 mile to the centroid of the hexagon or, equivalently, that jobs within one's own hexagon are

accessible with no dampening. Note that the distance between centroids of the two annexing hexagons is 1.075 miles, so the access to jobs in all hexagons other than one's own is damped by the inverse distance factor.

Table 1 summarizes the resulting employment accessibility variable.

Table 1: Descriptive Statistics: Accessibility to All Jobs

Variable	Obs (N)	Mean	Std. Dev.	Min	Max
<i>emp_acc</i>	14,877	6.264	4.648	0.023	32.837

Figure 5 shows the spatial distribution of the variable *emp_acc*. More than 80% of the households have an *emp_acc* less than 10. Note that from *emp_acc* and for the related variables that follow, the accessibility variables are normalized by dividing by 10,000, as shown in the formula above. The households with higher *emp_acc* values are located in the core area of Los Angeles and Orange counties.

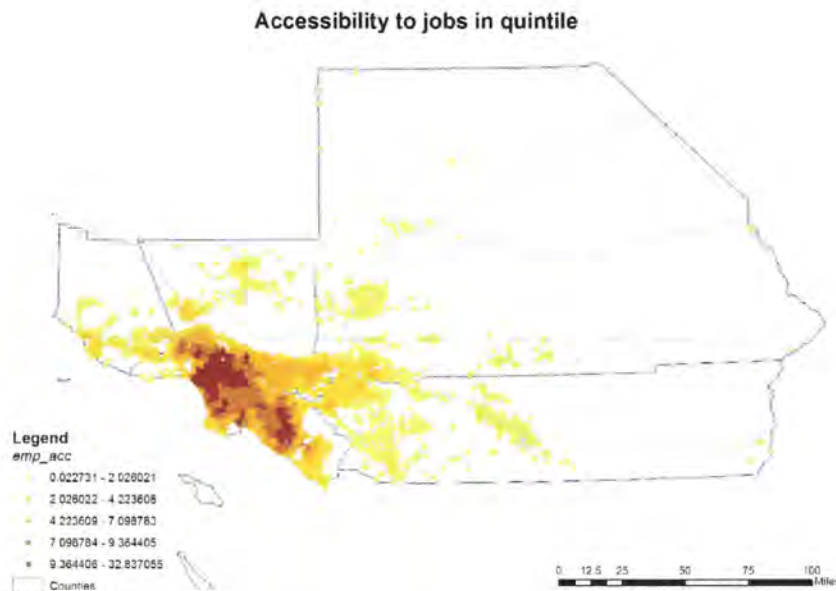


Figure 5 Spatial distribution of *emp_acc* for sample households

Accessibility to Jobs Located Inside and Outside Sub-centers

As discussed in Section III-A, the Los Angeles CSA is highly polycentric region with 46 employment sub-centers. The jobs in these employment sub-centers constitute 39.8% of the

total employment in the region. Theories from the economic geography argue that agglomeration economies will increase levels of productivity (Puga 2010) (Glaeser et al. 1992). Thus, the jobs located inside sub-centers might be more productive, or serve different economic functions, than those located outside the sub-centers. Similarly, sub-centers might allow patterns of trip chaining that might not be as easily realized outside of sub-centers. Hence, spatial accessibility to jobs located inside sub-centers might impact household VMT differently than does accessibility to jobs located outside sub-centers.

In order to test this hypothesis, we break the job accessibility index into multiple indices, measuring accessibility to jobs inside and outside employment sub-centers. We first create two accessibility indices: *emp_acc_ctr* for accessibility to jobs located inside employment sub-centers, and *emp_acc_nctr* for accessibility to jobs located outside employment sub-centers. Each is a gravity summation of access to employment from each hexagon “i”, with *emp_acc_ctr* only summed over jobs that are in the 46 sub-centers, while *emp_acc_nctr* is summed over all other hexagons (those not in sub-centers.) The descriptive statistics for these two indices are shown as Table 2 below:

Table 2: Descriptive Statistics – Accessibility to Jobs Within and Outside Employment Sub-Centers

Variable	Obs (N)	Mean	Std. Dev.	Min	Max
<i>emp_acc_ctr</i>	14,877	3.151	4.008	0.007	29.850
<i>emp_acc_nctr</i>	14,877	3.113	1.478	0.016	6.652

The map of the variable *emp_acc_ctr* is shown as Figure 6 below. Less than 10% of the total households in the sample have a value of *emp_acc_ctr* greater than 10. The households having the top-quintile values of this index are concentrated around the two biggest employment sub-centers: the hearts of Los Angeles County and Orange County.

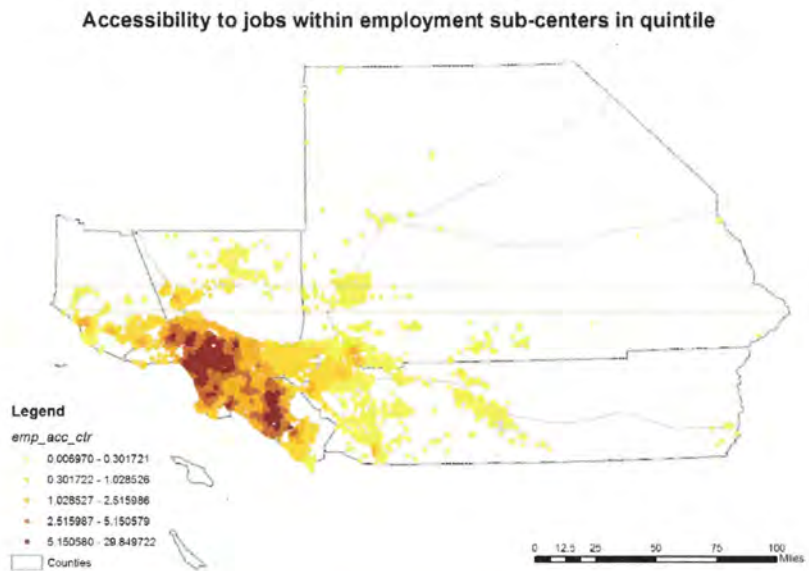


Figure 6 Spatial distribution of emp_acc_ctr for sample households

The map showing the spatial distribution of the variable *emp_acc_nctr* is Figure 7 below. The households with a higher value of the *emp_acc_nctr* variable are located in Los Angeles and Orange Counties.

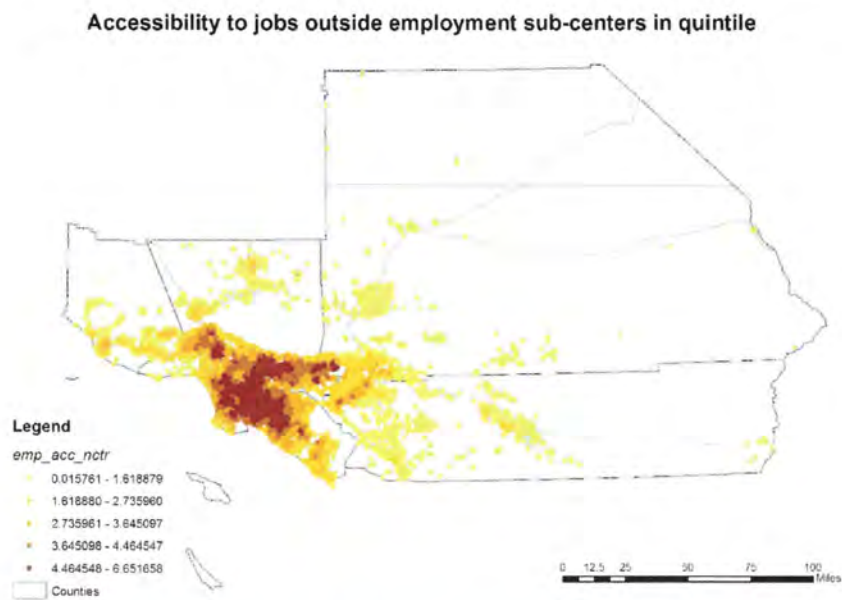


Figure 7 Spatial distribution of emp_acc_nctr for sample households

Accessibility to Jobs Located in Large and Small Sub-centers

As discussed in previous sections, the jobs in the 46 employment sub-centers are highly concentrated in the two largest sub-centers. The largest and second-largest employment sub-centers contain 33.2% and 18.2% of the total jobs located inside employment sub-centers, respectively. The size of the employment sub-center might impact the level of the agglomeration economies and possibly the nature of the land use – travel interaction from employment access to VMT. Thus, we further break the accessibility variables into three different indices: *emp_acc_ctr1* for accessibility to jobs within only the largest employment sub-center (Center 1), *emp_acc_ctr2* for accessibility to jobs within the 2nd largest employment sub-center (Center 2) and *emp_acc_ctrother* for accessibility to jobs within the 3rd to 46th employment sub-centers. As before, these variables are constructed so that they are strict subsets of the overall gravity variable (*emp_acc*), in the sense that hexagons are either in Center 1, Center 2, or all other centers. The descriptive statistics of these three new indices are shown in Table 3 below, and the maps of these three indices are shown in Figure 8 through Figure 10. Not surprisingly, the households with higher accessibility to jobs within the 1st and 2nd employment sub-centers are located near those centers, while the households with higher accessibility to jobs within the 3rd through the 46th largest sub-centers are predominantly located in the Los Angeles County.

Table 3: Descriptive Statistics – Accessibility to Jobs within the Largest, 2nd Largest and 3rd – 46th Largest Centers

Variable	Obs (N)	Mean	Std. Dev.	Min	Max
<i>emp_acc_ctr1</i>	14,877	1.526	3.657	0.002	28.745
<i>emp_acc_ctr2</i>	14,877	0.377	1.192	0.001	17.067
<i>emp_acc_ctrother</i>	14,877	1.247	1.395	0.003	7.922

Accessibility to jobs located in the largest employment sub-centers in quintile

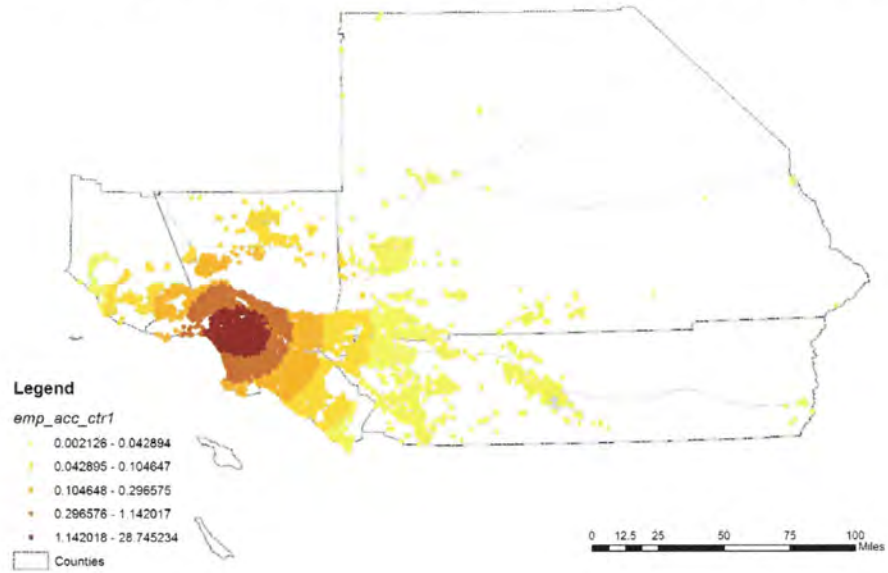


Figure 8 Spatial distribution of emp_acc_ctr1 for sample households

Accessibility to jobs located in the second-largest employment center in quintile

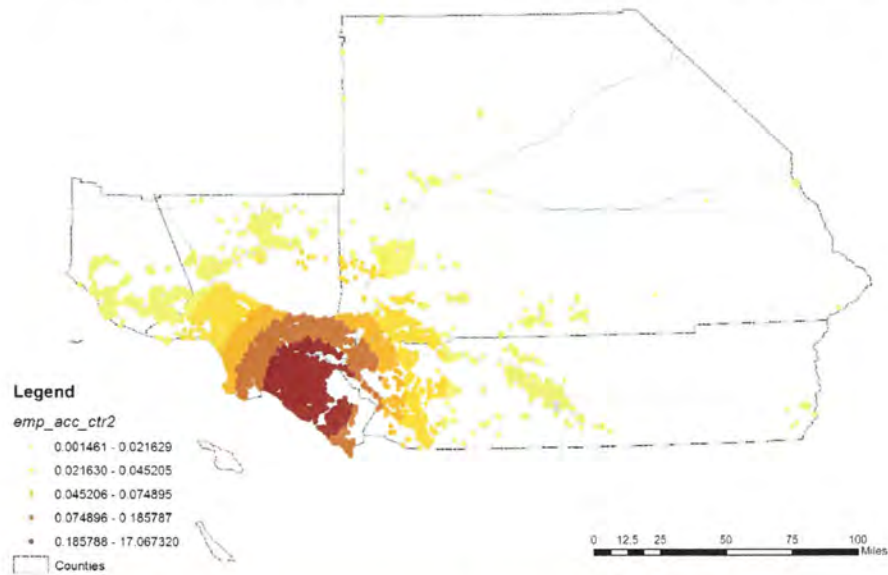


Figure 9 Spatial distribution of emp_acc_ctr2 for sample households

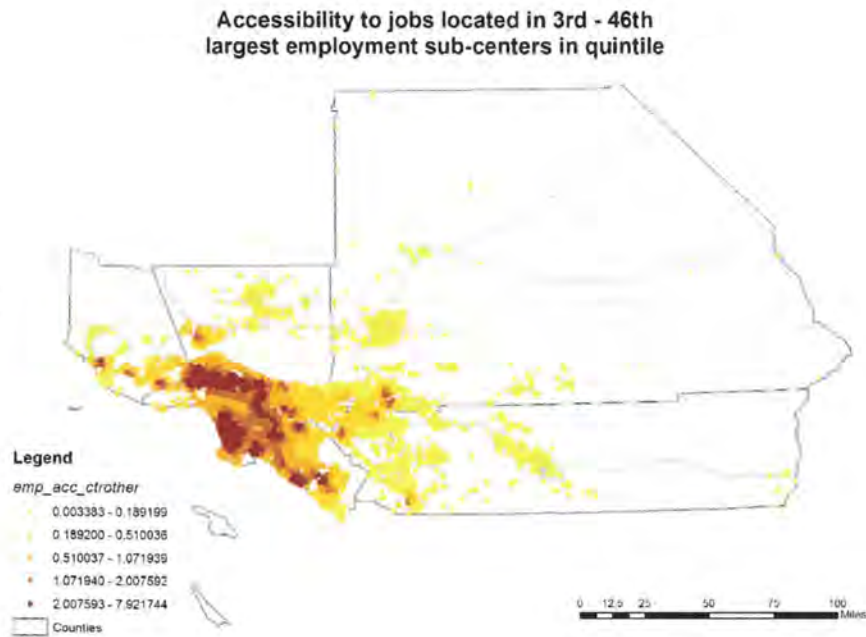


Figure 10 Spatial distribution of *emp_acc_ctrother* for sample households

Accessibility to Jobs Nearby (Within Five Miles) and Far From (Beyond Five Miles) the Household's Residence

The effect of regional access to jobs may function differently for access to jobs near versus jobs far from one's residence. The difference between commute travel versus local shopping may be sufficient to generate such a difference. To explore this, we adopt a standard from Salon (2013) , who divided the employment access gravity variable into access to jobs within five miles from a household's residence and beyond five miles from a household's residence.

To recap, the variables for accessibility, adjusted for jobs within and beyond five miles and for jobs in the largest sub-center, the second-largest sub-center, and all other sub-centers, are shown below. The variables are mutually exclusive, in the sense that any one hexagon is in the summation only for one variable, in the way shown below.

$$emp_acc = emp_acc_ctr1 + emp_acc_ctr2 + emp_acc_ctrother + emp_acc_nctr$$

$$emp_acc_ctr1 = emp_acc_ctr1_less5 + emp_acc_ctr1_more5$$

$$emp_acc_ctr2 = emp_acc_ctr2_less5 + emp_acc_ctr2_more5$$

$$emp_acc_ctrother = emp_acc_ctrother_less5 + emp_acc_ctrother_more5$$

$$emp_acc_nctr = emp_acc_nctr_less5 + emp_acc_nctr_more5$$

The variable *emp_acc_ctr1_less5* measures the accessibility to jobs located in the largest employment sub-center for jobs within five miles of a household's residence, *emp_acc_ctr1_more5* measures the accessibility to jobs located in largest employment sub-center when those jobs are beyond five miles from the household's residence. Similarly,

emp_acc_ctr2_less5 measures the accessibility to jobs located in the 2nd largest employment sub-center that are within five miles of a household’s residence and *emp_acc_ctr2_more5* measures the accessibility to jobs located in the 2nd largest employment sub-center and that are beyond five miles from the household’s residence; *emp_acc_ctrother_less5* measure the accessibility to jobs located in the 3rd through the 46th largest employment sub-centers and within five miles of a household’s residence, *emp_acc_ctrother_more5* measures the accessibility to jobs located in the 3rd through the 46th largest employment sub-center and beyond five miles of a household’s residence; *emp_acc_nctr_less5* measures the accessibility to jobs located outside employment sub-centers and within five miles of the household’s residence, *emp_acc_nctr_more5* measures the accessibility to jobs located outside employment sub-centers and beyond five miles of the household’s residence. The descriptive statistics for these 8 new indices are shown in Table 4 below.

Table 4: Descriptive Statistics – Accessibility to Jobs Less and More than 5 Miles from Residence

Variable	Obs (N)	Mean	Std. Dev.	Min	Max
<i>emp_acc_ctr1_less5</i>	14,877	1.122	3.451	0.000	27.999
<i>emp_acc_ctr1_more5</i>	14,877	0.404	0.458	0.002	2.087
<i>emp_acc_ctr2_less5</i>	14,877	0.238	1.089	0.000	16.766
<i>emp_acc_ctr2_more5</i>	14,877	0.140	0.199	0.001	1.053
<i>emp_acc_ctrother_less5</i>	14,877	0.817	1.284	0.000	7.382
<i>emp_acc_ctrother_more5</i>	14,877	0.430	0.285	0.003	1.064
<i>emp_acc_nctr_less5</i>	14,877	2.027	1.073	0.000	4.955
<i>emp_acc_nctr_more5</i>	14,877	1.086	0.511	0.013	2.039

The correlation matrix for the eight access variables is shown in Table 5 below.

Table 5: Correlation Matrix for Accessibility to Jobs Less and More than 5 Miles from Residence

	<i>emp_acc_ctr1_less5</i>	<i>emp_acc_ctr1_more5</i>	<i>emp_acc_ctr2_less5</i>	<i>emp_acc_ctr2_more5</i>	<i>emp_acc_ctr_other_less5</i>	<i>emp_acc_ctr_other_more5</i>	<i>emp_acc_nctr_less5</i>	<i>emp_acc_nctr_more5</i>
<i>emp_acc_ctr1_less5</i>	1.000							
<i>emp_acc_ctr1_more5</i>	0.395	1.000						
<i>emp_acc_ctr2_less5</i>	-0.071	-0.143	1.000					
<i>emp_acc_ctr2_more5</i>	-0.141	-0.222	0.453	1.000				
<i>emp_acc_ctr_other_less5</i>	-0.139	0.436	-0.088	-0.038	1.000			
<i>emp_acc_ctr_other_more5</i>	0.514	0.784	0.000	0.066	0.295	1.000		
<i>emp_acc_nctr_less5</i>	-0.057	0.386	0.050	0.294	0.292	0.553	1.000	
<i>emp_acc_nctr_more5</i>	0.263	0.560	0.123	0.364	0.282	0.820	0.703	1.000

The maps showing the distribution of the eight access variables are shown in Figure 11 through Figure 18 below.

Accessibility to jobs within 5 miles of residence and located in the largest employment sub-center in quintile

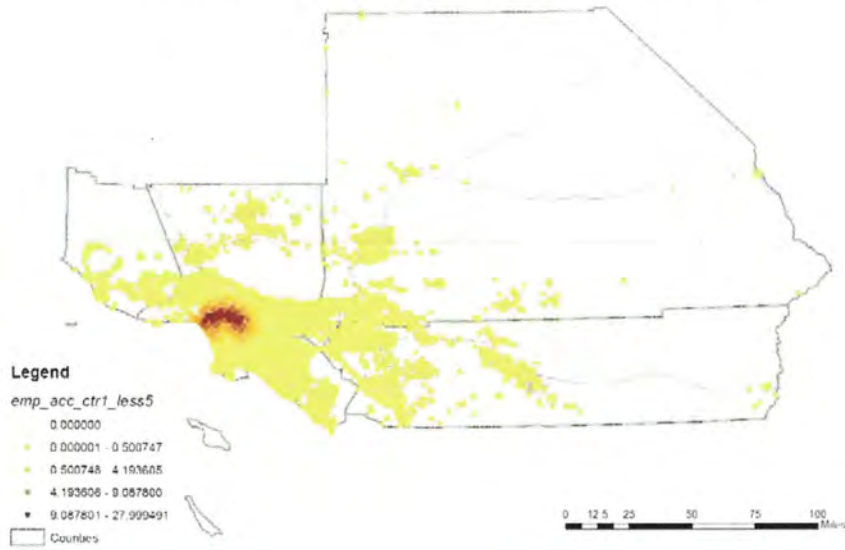


Figure 11 Spatial distribution of emp_acc_ctr1_less5 for sample households

Accessibility to jobs beyond 5 miles of residence and located in the largest employment sub-center in quintile

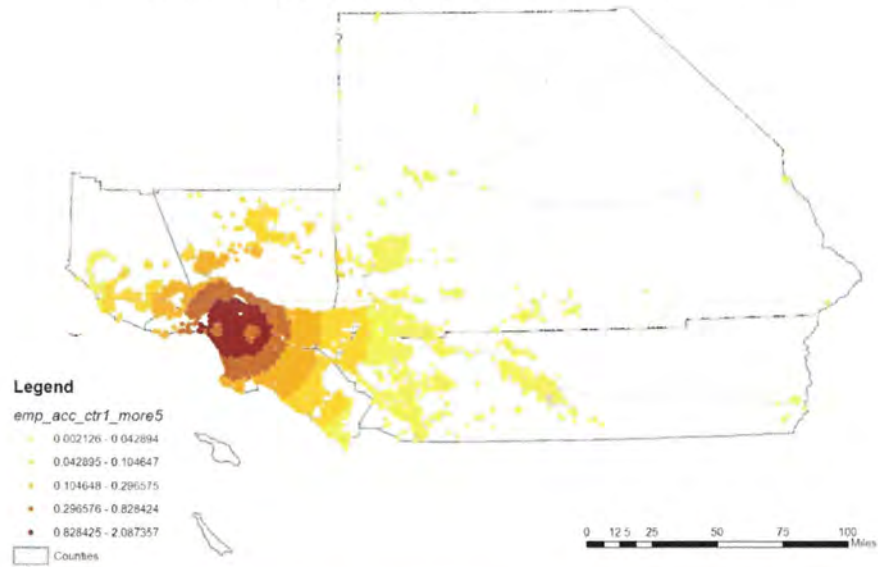


Figure 12 Spatial distribution of emp_acc_ctr1_more5 for sample households

Accessibility to jobs within 5 miles of residence and located in the second-largest employment sub-center in quintile

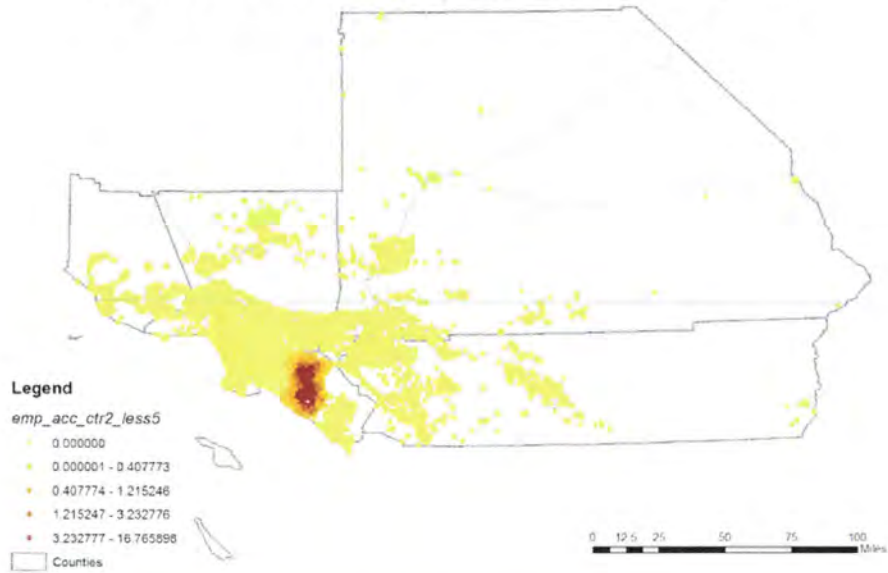


Figure 13 Spatial distribution of emp_acc_ctr2_less5 for sample households

Accessibility to jobs beyond 5 miles of residence and located in the second-largest employment sub-center in quintile

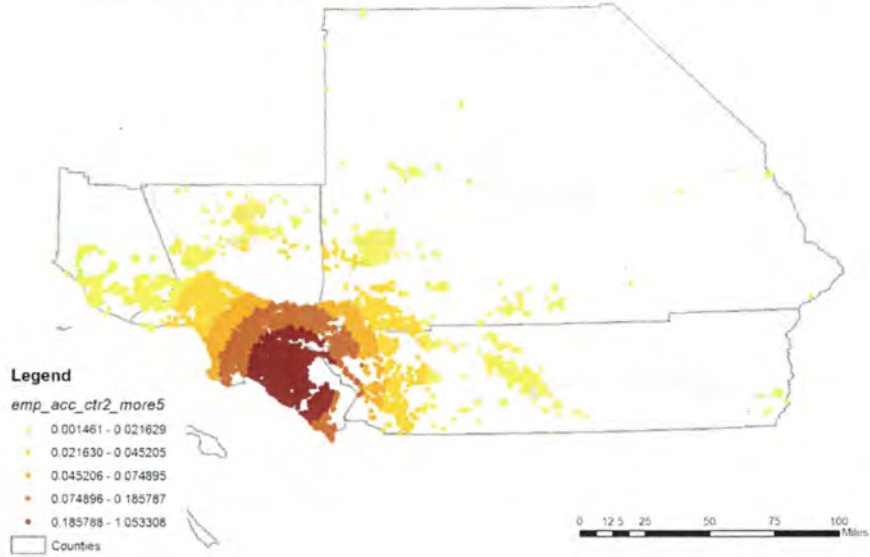


Figure 14 Spatial distribution of emp_acc_ctr2_more5 for sample households

Accessibility to jobs within 5 miles of residence and located in the 3rd - 46th largest employment sub-center in quintile

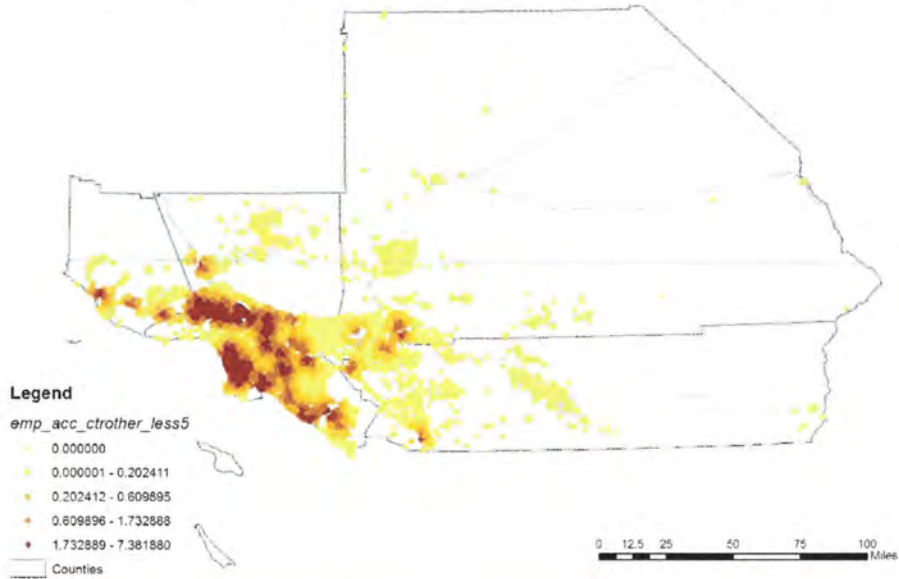


Figure 15 Spatial distribution of emp_acc_ctrother_less5 for sample households

Accessibility to jobs within 5 miles of residence and located in the largest employment sub-center in quintile

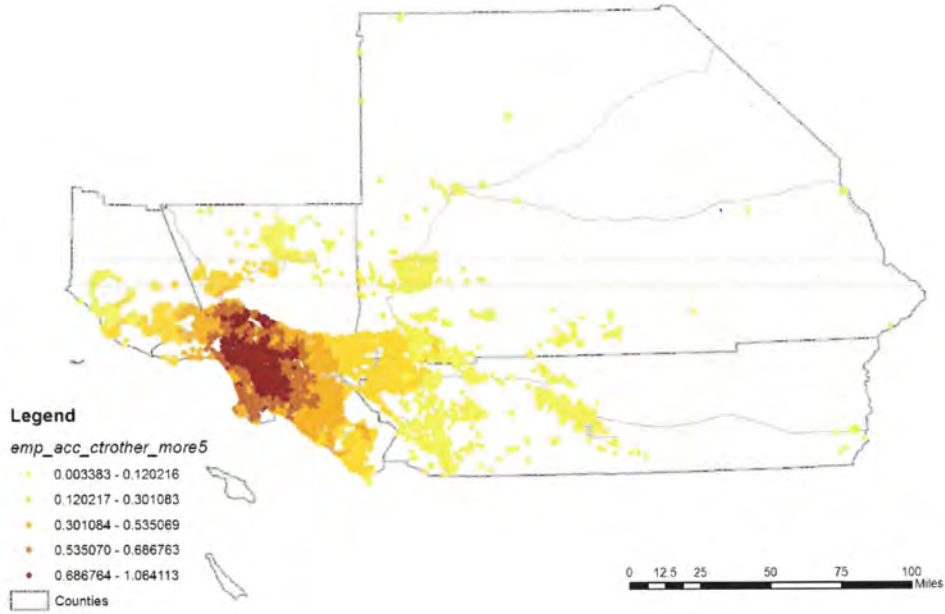


Figure 16 Spatial distribution of *emp_acc_ctrother_more5* for sample households

Accessibility to jobs within 5 miles of residence and located in the largest employment sub-center in quintile

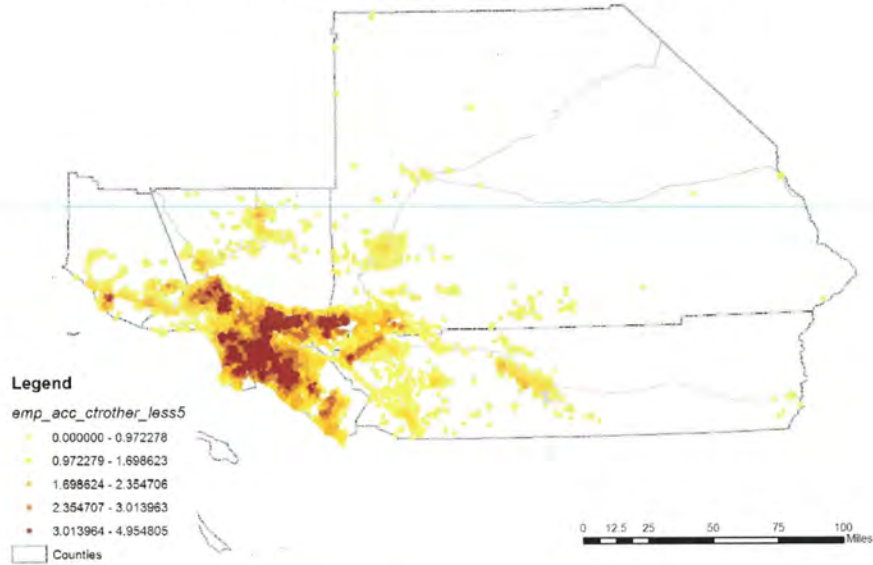


Figure 17 Spatial distribution of *emp_acc_nctr_less5* for sample households

Accessibility to jobs within 5 miles of residence and located in the largest employment sub-center in quintile

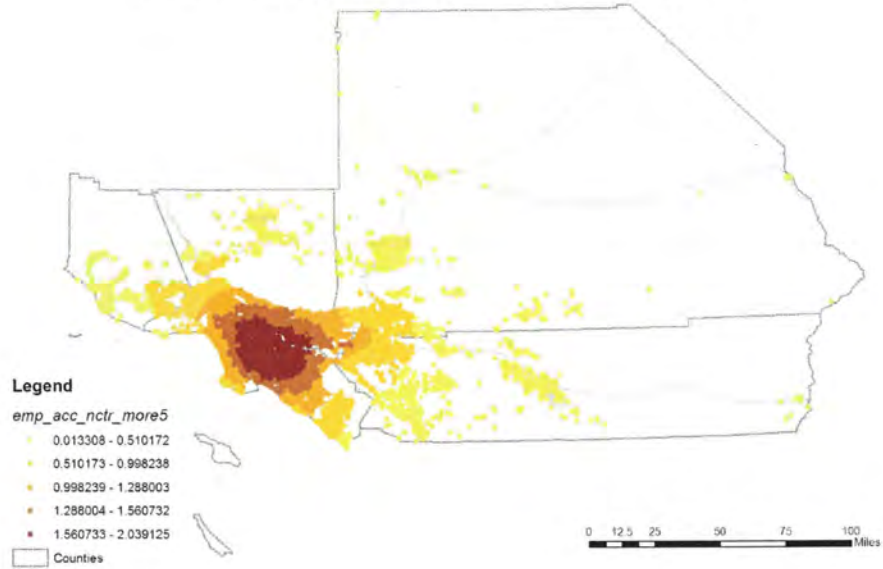


Figure 18 Spatial distribution of *emp_acc_nctr_more5* for sample households

Regression Specification

In order to measure the impact of accessibility to jobs in different measurement, we estimated four groups of regression models, following the formula below:

$$VMT_i = \beta_0 + emp_acc_i \cdot \beta_1 + X_i \cdot \beta_2 + \varepsilon_i$$

Where VMT indicates the household level daily vehicle-miles traveled, the vector *emp_acc_i* indicates the job accessibility variables, and the vector *X_i* indicates other control variables theoretically related to the level of household VMT. The definitions and sources of all the dependent and independent variables are shown in Table 6. The *X_i* vector includes: number of vehicles in the household, household income (dummy variables in the categories shown in Table 7) household size and residential density at the census tract level. Each observation in the regression is a household, and the access variables are all generated relative to the household's location and so measure employment access from that household's location. The regressions were estimated using a Tobit specification. The descriptive statistics of the dependent and independent variables are in Table 7 below.

Table 6: Definition and Data Source of Dependent and Independent Variables

Variable	Definition	Calculation	Data source
<i>vmt</i>	household VMT	N/A	CHTS 2010
<i>hhveh</i>	Number of vehicles in household	N/A	CHTS 2010
<i>hhinc_1</i>	Factor variable for household income	= 1 if household income is less than \$10,000	
<i>hhinc_2</i>	Factor variable for household income	= 1 if household income is between \$10,000 and \$24,999	
<i>hhinc_3</i>	Factor variable for household income	= 1 if household income is between \$25,000 and \$34,999	
<i>hhinc_4</i>	Factor variable for household income	= 1 if household income is between \$35,000 and \$49,999	
<i>hhinc_5</i>	Factor variable for household income	= 1 if household income is between \$50,000 and \$74,999	
<i>hhinc_6</i>	Factor variable for household income	= 1 if household income is between \$75,000 and \$99,999	
<i>hhinc_7</i>	Factor variable for household income	= 1 if household income is between \$100,000 and \$149,999	
<i>hhinc_8</i>	Factor variable for household income	= 1 if household income is between \$150,000 and \$199,999	
<i>hhinc_9</i>	Factor variable for household income	= 1 if household income is between \$200,000 and \$249,999	
<i>hhinc_10</i>	Factor variable for household income	= 1 if household income is \$250,000 or more	CHTS 2010
<i>hhsize</i>	Number of persons in household	N/A	CHTS 2010
<i>density</i>	Residential density at the census tract level (1k per square mile)	N/A	CHTS 2010 and 2010 Census SF1
<i>d_la_or</i>	flag for Los Angeles and Orange Counties	N/A	CHTS 2010
<i>emp_acc</i>	accessibility to all jobs	$emp_acc_i = \left(\sum_{j \neq i} \frac{E_j}{D_{ij}^2} + E_i \right) \cdot \frac{1}{10,000}$ <p>E_i: number of jobs in the hexagon of household i's residence E_j: number of jobs in hexagon j ($j \neq i$) D_{ij}: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009

Table 6: Definition and Data Source of Dependent and Independent Variables Continued

Variable	Definition	Calculation	Data source
<i>emp_acc_ctr</i>	accessibility to jobs located inside employment sub-centers	$emp_acc_ctr_i = \left(\sum_{j \neq i} \frac{E_{cj}}{D_{ij}^2} + E_{ci} \right) \cdot \frac{1}{10,000}$ <p><i>E_{ci}</i>: number of jobs in the hexagon of the household <i>i</i>'s residence and located in employment sub-centers <i>E_{cj}</i>: number of jobs in hexagon <i>j</i> (<i>j</i>≠<i>i</i>) and located in employment sub-centers <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon <i>i</i> and hexagon <i>j</i></p>	CHTS 2010 and NETS 2009
<i>emp_acc_nctr</i>	accessibility to jobs located outside employment sub-centers	$emp_acc_nctr_i = \left(\sum_{j \neq i} \frac{E_{ncj}}{D_{ij}^2} + E_{nci} \right) \cdot \frac{1}{10,000}$ <p><i>E_{nci}</i>: number of jobs in the hexagon of the household <i>i</i>'s residence and located outside employment sub-centers <i>E_{ncj}</i>: number of jobs in hexagon <i>j</i> (<i>j</i>≠<i>i</i>) and located outside employment sub-centers <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon <i>i</i> and hexagon <i>j</i></p>	CHTS 2010 and NETS 2009
<i>emp_acc_ctr1</i>	accessibility to jobs located inside the largest employment sub-center	$emp_acc_ctr1_i = \left(\sum_{j \neq i} \frac{E_{c1j}}{D_{ij}^2} + E_{c1i} \right) \cdot \frac{1}{10,000}$ <p><i>E_{c1i}</i>: number of jobs in the hexagon of the household <i>i</i>'s residence and located in the largest employment sub-center <i>E_{c1j}</i>: number of jobs in hexagon <i>j</i> (<i>j</i>≠<i>i</i>) and located in the largest employment sub-center <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon <i>i</i> and hexagon <i>j</i></p>	CHTS 2010 and NETS 2009
<i>emp_acc_ctr2</i>	accessibility to jobs located inside the second-largest employment sub-center	$emp_acc_ctr2_i = \left(\sum_{j \neq i} \frac{E_{c2j}}{D_{ij}^2} + E_{c2i} \right) \cdot \frac{1}{10,000}$ <p><i>E_{c2i}</i>: number of jobs in the hexagon of the household <i>i</i>'s residence and located in the second-largest employment sub-center <i>E_{c2j}</i>: number of jobs in hexagon <i>j</i> (<i>j</i>≠<i>i</i>) and located in the second-largest employment sub-center <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon <i>i</i> and hexagon <i>j</i></p>	CHTS 2010 and NETS 2009

Table 6: Definition and Data Source of Dependent and Independent Variables Continued

Variable	Definition	Calculation	Data source
<i>emp_acc_ctrother</i>	accessibility to jobs located inside the 3rd - 46th largest employment sub-center	$emp_acc_ctrother_i = \left(\sum_{j \neq i} \frac{E_{cotherj}}{D_{ij}^2} + E_{cotheri} \right) \cdot \frac{1}{10,000}$ <p><i>E_{cotheri}</i>: number of jobs in the hexagon of the household i's residence and located in the 3rd - 46th largest employment sub-centers <i>E_{cotherj}</i>: number of jobs in hexagon j (j≠i) and located in the 3rd - 46th largest employment sub-centers <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009
<i>emp_acc_ctr1_less5</i>	accessibility to jobs within 5 miles of residence and in the largest sub-center	$emp_acc_ctr1_less5_i = \left(\sum_{j \neq i} \frac{E_{c1_less5j}}{D_{ij}^2} + E_{c1i} \right) \cdot \frac{1}{10,000}$ <p><i>E_{c1i}</i>: number of jobs in the hexagon of the household i's residence and located in the largest employment sub-center <i>E_{c1_less5j}</i>: number of jobs in hexagon j (j≠i) and located in the largest employment sub-center and within 5 miles of residence <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009
<i>emp_acc_ctr1_more5</i>	accessibility to jobs beyond 5 miles of residence and in the largest sub-center	$emp_acc_ctr1_more5_i = \left(\sum_{j \neq i} \frac{E_{c1_more5j}}{D_{ij}^2} \right) \cdot \frac{1}{10,000}$ <p><i>E_{c1_more5j}</i>: number of jobs in hexagon j (j≠i) and located in the largest employment sub-center and beyond 5 miles of residence <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009
<i>emp_acc_ctr2_less5</i>	accessibility to jobs within 5 miles of residence and in the second-largest sub-center	$emp_acc_ctr2_less5_i = \left(\sum_{j \neq i} \frac{E_{c2_less5j}}{D_{ij}^2} + E_{c2i} \right) \cdot \frac{1}{10,000}$ <p><i>E_{c2i}</i>: number of jobs in the hexagon of the household i's residence and located in the second-largest employment sub-center <i>E_{c2_less5j}</i>: number of jobs in hexagon j (j≠i) and located in the second-largest employment sub-center and within 5 miles of residence <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009

Table 6: Definition and Data Source of Dependent and Independent Variables Continued

Variable	Definition	Calculation	Data source
<i>emp_acc_ctr2_more5</i>	accessibility to jobs beyond 5 miles of residence and in the second-largest sub-center	$emp_acc_ctr2_more5_i = \left(\sum_{j \neq i} \frac{E_{c2_more5j}}{D_{ij}^2} \right) \cdot \frac{1}{10,000}$ <p><i>E_{c2_less5j}</i>: number of jobs in hexagon j (j≠i) and located in the second-largest employment sub-center and beyond 5 miles of residence <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009
<i>emp_acc_ctrother_less5</i>	accessibility to jobs within 5 miles of residence and in the 3rd - 46th largest sub-centers	$emp_acc_ctrother_less5_i = \left(\sum_{j \neq i} \frac{E_{ctrother_less5j}}{D_{ij}^2} + E_{ctrotheri} \right) \cdot \frac{1}{10,000}$ <p><i>E_{ctrotheri}</i>: number of jobs in the hexagon of the household i's residence and located in the 3rd – 46th largest employment sub-centers <i>E_{ctrother_less5j}</i>: number of jobs in hexagon j (j≠i) and located in the 3rd – 46th largest employment sub-centers and within 5 miles of residence <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009
<i>emp_acc_ctrother_more5</i>	accessibility to jobs beyond 5 miles of residence and in the 3rd - 46th largest sub-centers	$emp_acc_ctrother_more5_i = \left(\sum_{j \neq i} \frac{E_{ctrother_more5j}}{D_{ij}^2} \right) \cdot \frac{1}{10,000}$ <p><i>E_{c2_more5j}</i>: number of jobs in hexagon j (j≠i) and located in the 3rd – 46th largest employment sub-centers and beyond 5 miles of residence <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009
<i>emp_acc_nctr_less5</i>	accessibility to jobs within 5 miles of residence and outside sub-centers	$emp_acc_nctr_less5_i = \left(\sum_{j \neq i} \frac{E_{nctr_less5j}}{D_{ij}^2} + E_{nctri} \right) \cdot \frac{1}{10,000}$ <p><i>E_{nctri}</i>: number of jobs in the hexagon of the household i's residence and located outside employment sub-centers <i>E_{nctr_less5j}</i>: number of jobs in hexagon j (j≠i) and located outside employment sub-centers and within 5 miles of residence <i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009

Table 6: Definition and Data Source of Dependent and Independent Variables Continued

Variable	Definition	Calculation	Data source
<i>emp_acc_nctr_more5</i>	accessibility to jobs beyond 5 miles of residence and outside sub-centers	$emp_acc_nctr_more5_i = \left(\sum_{j \neq i} \frac{E_{nctr_more5j}}{D_{ij}^2} \right) \cdot \frac{1}{10,000}$ <p><i>E_{nctr_more5j}</i>: number of jobs in hexagon j (j≠i) and located in the 3rd – 46th largest employment sub-centers and beyond 5 miles of residence</p> <p><i>D_{ij}</i>: distance (in miles) between the centroids of hexagon i and hexagon j</p>	CHTS 2010 and NETS 2009

Table 7: Descriptive Statistics of Dependent and Independent Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
household VMT	35.55	40.90	0	199.99	35.55
Number of vehicles in household	1.85	1.00	0	8	1.85
household income					
<i>less than \$ 10,000</i>			(reference term)		
<i>\$10,000 to \$24,999</i>	0.13	0.33	0	1	0.13
<i>\$25,000 to \$34,999</i>	0.09	0.28	0	1	0.09
<i>\$35,000 to \$49,999</i>	0.12	0.32	0	1	0.12
<i>\$50,000 to \$74,999</i>	0.17	0.38	0	1	0.17
<i>\$75,000 to \$99,999</i>	0.15	0.36	0	1	0.15
<i>\$100,000 to \$149,999</i>	0.17	0.37	0	1	0.17
<i>\$150,000 to \$199,999</i>	0.07	0.26	0	1	0.07
<i>\$200,000 to \$249,999</i>	0.03	0.17	0	1	0.03
<i>\$250,000 or more</i>	0.03	0.18	0	1	0.03
household size	2.66	1.44	1	8	2.66
Residential density at the census tract level (1k per square mile)	8.52	8.07	0.001	94.49	8.52
flag for Los Angeles and Orange Counties	0.70	0.46	0	1.00	0.70

We estimated four groups of regressions, based on the strategy shown in Figure 19 below. Specifically, the first group of regressions focuses only on accessibility to all jobs, in the second regression group we broke the single index into two variables to measure accessibility to jobs inside and outside sub-centers, in the third group of regressions we further broke the accessibility variable into measures of access to jobs within the largest, second-largest, and the 3rd-46th largest sub-centers, while in the fourth group of regressions we split the indices into accessibility measures for jobs within and beyond five miles of a household's residence. In each group of regressions, we estimated models for all households, households in coastal counties (Los Angeles and Orange) and households in inland counties (Ventura, Riverside and San Bernardino). While Ventura is geographically a coastal county, its suburban character is more similar to Riverside and San Bernardino and hence it is grouped with the inland counties.

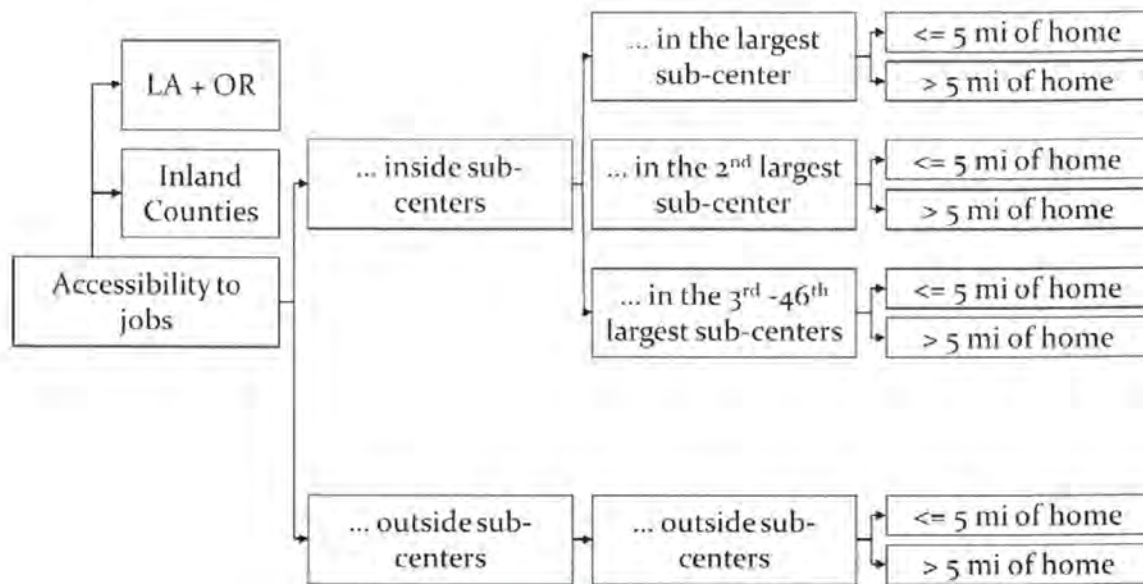


Figure 19 Modeling strategies

As shown in Figure 3 in Section 3, the distribution of household-level VMT is left-censored, more than 25% households in our sample have zero VMT on the survey day. Such a distribution violates the basic assumption of the ordinary least square (OLS) models and OLS will give biased estimation results. Thus, we used Tobit regression models. Tobit regression is designed to estimate regressions with censored dependent variables using a Maximum Likelihood Estimation method.

We estimated elasticities based on the regression results, to provide a unit-free measurement of the magnitude of impact of accessibility on household-level VMT. An elasticity value of x can be interpreted as the percentage change in the dependent variable (VMT) associated with a 1% change in the independent variable of interest. Since the Tobit model is not linear, we estimate the elasticity of household VMT with respect to accessibility following the method of Boarnet et al. (2011) shown in the formula below:

$$e = \frac{1}{n} \sum_i me_i * \frac{accessibility_i}{VMT_i}$$

where:

e = elasticity

me_i = marginal effect for household i :

for Tobit regressions:

$$me_i = \hat{p}(VMT_i > 0) * \beta$$

n = number of observations

Regression Results

Accessibility to All Jobs

The output of the regression models for accessibility to all jobs is shown below as Model 1 through Model 3 in Table 8. Values for elasticities are listed below the coefficients of the corresponding variables. In all of the regression tables, the 95% confidence interval is shown in brackets below the regression coefficients. The regression tables only report the results on the accessibility variables, to highlight the effect of interest. Regression results for all of the control variables (the demographic variables and census tract population density) are in the appendix of this report.

Table 8: Regression Models for Accessibility to All Jobs

	All counties	Coastal counties	Inland counties
	Model 1	Model 2	Model 3
Accessibility to jobs (<i>emp_acc</i>)	-0.815***	-0.854***	-1.414*
	[-1.041,-0.588]	[-1.103,-0.606]	[-2.920,0.093]
<i>elasticity</i>	-0.249	-0.347	-0.140
Pseudo R-square	0.025	0.028	0.018
N	13475	9361	4114

Note: Control variables not shown, 95% confidence interval in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Accessibility to Centered and Non-centered Jobs

The result of the regression models for accessibility to jobs located inside and outside employment sub-centers is shown below as Model 4 through Model 6 in Table 9. Values of elasticity are listed below the coefficients of the corresponding variables. Note that for the coastal counties, the 95% confidence intervals for the two accessibility variables, to jobs in and outside of sub-centers, do not overlap. Cases where the distinct sub-center access variables have coefficients that do not overlap will be highlighted in yellow. The interpretation is that, in Table 9 the results indicate that, in Los Angeles and Orange Counties, access to non-centered jobs has a larger impact on VMT than does access to jobs in employment sub-centers (the elasticity of *emp_acc_nctr* is -0.347, twice the size of the elasticity of *emp_acc_ctr* which is -0.174.)

Table 9: Regression Models for Accessibility to Jobs Inside and Outside Employment Sub-Centers

	All counties	Coastal counties	Inland counties
	Model 4	Model 5	Model 6
Accessibility to jobs in the sub-centers – (<i>emp_acc_ctr</i>)	-0.722*** [-0.975,-0.468]	-0.784*** [-1.037,-0.531]	-2.4 [-6.739,1.939]
<i>elasticity</i>	-0.111	-0.174	
Accessibility to jobs outside sub-centers (<i>emp_acc_nctr</i>)	-1.258*** [-1.843,-0.673]	-1.863*** [-2.623,-1.104]	-1.149 [-3.009,0.711]
<i>elasticity</i>	-0.191	-0.347	
Pseudo R-square	0.025	0.029	0.018
N	13475	9361	4114

Note: Control variables not shown, 95% confidence interval in brackets, * p<0.10, ** p<0.05, *** p<0.01

Accessibility to Jobs in 1st, 2nd, Other Sub-centers and Non-centered Jobs

The output of the regression models for accessibility to jobs located inside the largest sub-center, inside the second-largest sub-center, inside the 3rd – 46th largest sub-centers, and outside employment sub-centers is shown below as Model 7 through Model 9 in Table 10. Values of elasticities are listed below the coefficients of the corresponding variables. In the coastal counties, access to non-centered jobs again has the largest magnitude on VMT, an elasticity of -0.305. This suggests that doubling the access to non-centered jobs in Los Angeles and Orange Counties will reduce household VMT by, on average, 30.5% for households residing in those counties. In the inland counties, note the positive coefficient on access to the second-largest center (*emp_acc_ctr2*). In Riverside and San Bernardino Counties, many workers commute to Orange County, and so in that specific case it is not surprising that improved access to the sub-center in central Orange County is associated with higher VMT. Those workers and persons who commute from the inland counties to the second-largest sub-center (a long drive from any location in the inland counties) are likely the same persons who have relatively good access to that 2nd largest job center. Among the statistically significant effects in the inland counties for the access variables with a negative sign, again access to non-centered jobs has the largest elasticity, -0.26.

Table 10: Regression Models for Accessibility to Jobs from Different Employment Sub-Centers

	All counties	Coastal counties	Inland counties
	Model 7	Model 8	Model 9
Accessibility to jobs in the largest sub-center – (<i>emp_acc_ctr1</i>)	-0.640*** [-0.911,-0.368]	-0.697*** [-0.960,-0.433]	-2.808 [-54.075,48.459]
<i>elasticity</i>	-0.047	-0.076	
Accessibility to jobs in the second-largest sub-center – (<i>emp_acc_ctr2</i>)	-0.926*** [-1.602,-0.251]	-1.128*** [-1.772,-0.485]	79.091*** [33.593,124.589]
<i>elasticity</i>	-0.017	-0.029	0.140
Accessibility to jobs in the 3rd - 46th largest sub-center – (<i>emp_acc_ctrother</i>)	-1.196*** [-1.841,-0.552]	-1.418*** [-2.058,-0.778]	-2.266 [-6.754,2.222]
<i>elasticity</i>	-0.075	-0.123	
Accessibility to jobs outside sub-centers – (<i>emp_acc_nctr</i>)	-1.041*** [-1.678,-0.405]	-1.640*** [-2.423,-0.858]	-3.146*** [-5.429,-0.862]
<i>elasticity</i>	-0.158	-0.305	-0.260
Pseudo R-square	0.025	0.029	0.018
N	13475	9361	4114

Note: Control variables not shown, 95% confidence interval in brackets, * p<0.10, ** p<0.05, *** p<0.01

Accessibility to Jobs Within and Beyond Five Miles of Residence

The output of the regression models for accessibility to jobs located within and beyond five miles of residence and inside the largest center, inside the 2nd largest center, inside the 3rd – 46th largest center and outside employment sub-centers is shown below as Model 10 through Model 12 in Table 11. In addition, Table 11 also has a Model 13 that only includes the significant access variables from Model 11. This Model 13 will be used for policy simulations, in the next section of this report. Values of elasticity are listed below the coefficients of the corresponding variables.

Table 11: Regression Models for Accessibility to Jobs from Different Employment Sub-Centers with 5-Mile Break Points

	All counties	Coastal counties	Inland counties	Coastal counties
	Model 10	Model 11	Model 12	Model 13
Accessibility to jobs within 5 miles of residence and in the largest sub-center – (<i>emp_acc_ctr1_less5</i>)	-0.567*** [-0.927,-0.208]	-0.433** [-0.782,-0.083]	0 [0.000,0.000]	-0.449** [-0.798,-0.100]
<i>elasticity</i>	-0.0309	-0.0349		
Accessibility to jobs beyond 5 miles of residence and in the largest sub-center – <i>emp_acc_ctr1_more5</i>	-1.123 [-4.448,2.201]	-1.015 [-4.127,2.096]	-16.26 [-142.425,109.905]	
<i>elasticity</i>				
Accessibility to jobs within 5 miles of residence and in the second-largest sub-center – (<i>emp_acc_ctr2_less5</i>)	-1.309*** [-2.125,-0.493]	-1.237*** [-1.997,-0.477]	0 [0.000,0.000]	-1.304*** [-1.996,-0.612]
<i>elasticity</i>	-0.015	-0.021		
Accessibility to jobs beyond 5 miles of residence and in the second-largest sub-center – (<i>emp_acc_ctr2_more5</i>)	-1.073 [-6.583,4.437]	-3.2 [-8.630,2.230]	24.045 [-42.612,90.701]	
<i>Elasticity</i>				
Accessibility to jobs within 5 miles of residence and in the 3rd - 46th largest sub-centers – (<i>emp_acc_ctrother_less5</i>)	-1.026*** [-1.777,-0.275]	-1.167*** [-1.887,-0.446]	-2.212 [-6.848,2.423]	-1.200*** [-1.873,-0.526]
<i>elasticity</i>	-0.0428	-0.0684		
Accessibility to jobs beyond 5 miles of residence and in the 3rd - 46th largest sub-centers – (<i>emp_acc_ctrother_more5</i>)	-9.457** [-17.100,-1.814]	-12.257*** [-20.610,-3.905]	-7.797 [-78.111,62.516]	-9.992*** [-15.655,-4.330]
<i>Elasticity</i>	-0.196	-0.345		
Accessibility to jobs within 5 miles of residence and outside sub-centers – (<i>emp_acc_nctr1_less5</i>)	-2.355*** [-3.500,-1.210]	-1.628** [-2.903,-0.353]	-4.738*** [-7.440,-2.035]	-1.411** [-2.560,-0.262]
<i>Elasticity</i>	-0.234	-0.195	-0.271	
Accessibility to jobs beyond 5 miles of residence and outside sub-centers – (<i>emp_acc_nctr1_more5</i>)	5.694*** [2.141,9.247]	2.705 [-1.182,6.592]	8.926 [-3.400,21.253]	
<i>elasticity</i>	0.302			
Pseudo R-square	0.025	0.029	0.018	0.029
N	13475	9361	4114	9361

Note: Control variables not shown, 95% confidence interval in brackets, * p<0.10, ** p<0.05, *** p<0.01

The general pattern from the earlier tables is repeated. Access to non-centered jobs has a larger association with VMT reduction than does access to centered jobs in the coastal counties. In the coastal counties, that effect is primarily a short-distance (within five miles) phenomenon. In the inland counties, access to non-centered jobs has the largest elasticity, again for jobs within five miles. Note that residents of the inland counties are never within 5

miles of the two largest sub-centers. In short, Table 11 indicates that the largest association (in terms of magnitude) with VMT is from non-centered jobs within five miles of a household's residence. Interpreting this table literally (which is too naïve for a policy prescription), one could say that increasing access to non-centered jobs within five miles from a household's residence would be the most impactful way to reduce VMT from among the employment access variables. Of course, this assumes that the relationships in Table 11 can be interpreted as causal relationships. We caution that additional research into whether the relationships in Table 11 are causal as opposed to associative may be warranted, subject to the discussion in the literature review section of this report.

Policy Simulation

In this section we simulate the impact of locational factors: employment accessibility and residential density on vehicle miles traveled. We take a hypothetical household in the centroids of their own communities: Simi Valley, Culver City, Laguna Hills, Anaheim, Moreno Valley, Riverside and Koreatown in Los Angeles, and calculate predicted household VMT at each of those locations. The specific locations of the centroids are shown in Figure 20 below.



Figure 20 Location of hypothetical households

In order to control for the socio-demographic factors, we use the average of the 13,745 households in the models as values of the socio-demographic variables for the hypothetical household. The specific values for these variables – number of vehicles in the household, number of people in the household, and household income – are shown in Table 12 below.

Table 12: Policy Simulation for Hypothetical Household in Seven Locations

Community	Model 12 Prediction	Model 13 Prediction	Model 10 Prediction	Number of Vehicles	Household Income	Number of people	Residential Density (in 1,000)
Simi Valley	.	41.87	38.55	1.85	\$50,000 to \$74,999	2.67	9.09
Culver City	.	35.39	33.61	1.85	\$50,000 to \$74,999	2.67	6.65
Laguna Hills	.	41.69	38.85	1.85	\$50,000 to \$74,999	2.67	4.88
Anaheim	.	36.38	36.84	1.85	\$50,000 to \$74,999	2.67	8.18
Moreno Valley	42.37	.	43.70	1.85	\$50,000 to \$74,999	2.67	2.13
Riverside	38.80	.	41.05	1.85	\$50,000 to \$74,999	2.67	4.61
Koreatown, Los Angeles	.	23.17	23.32	1.85	\$50,000 to \$74,999	2.67	70.45

Table 12 also includes the predicted household-level VMT for the household with the given average socio-demographic variables and the location-specific variables (density and accessibilities to jobs) using different models. Note that the location-specific variables change in each location, but the household demographic characteristics are constant across the locations. Recall that Model 12 is specifically for Riverside, San Bernardino and Ventura Counties, Model 13 is specifically for Los Angeles and Orange Counties, and Model 10 is for all the five counties. The prediction using Model 10 shows that the hypothetical household living in an exurban community like Moreno Valley drives 43.7 miles on average per day, and their household-level VMT would be 23.3 miles per day if the same household lived in Koreatown in Los Angeles. The regression predicts that the higher population density and higher accessibility to jobs in Koreatown is associated with predicted household VMT that is 46.6 percent lower than the predicted VMT of the same household living in Moreno Valley.

Conclusion and Discussions

In this report we provided a closer examination of how accessibility to jobs is associated with household-level vehicle miles traveled (VMT). The brief conclusion, based on the results of the four-step analysis, is below:

- Accessibility to jobs outside employment sub-centers often has a larger impact on VMT than the accessibility to jobs inside the sub-centers. An exception is in Table 11, Model 11, where the largest elasticity for the coastal counties is for access to jobs in the 3rd through 46th sub-centers and beyond five miles from a household’s residence. Note, overall, that jobs in sub-centers have independent effects associated with VMT, even though the magnitude is often smaller than the elasticity for jobs not in sub-centers.
- The effect of accessibility on household VMT varies in core counties and periphery counties. The VMT for households in coastal counties (Los Angeles and Orange) is more sensitive to accessibility to jobs than those in inland counties (Ventura, San Bernardino and Riverside). In both sets of counties, access to non-centered jobs has a larger

magnitude of association with VMT than does access to jobs in employment sub-centers.

- Accessibility to jobs within 5 miles from one's residence has a larger association with household VMT than accessibility to jobs beyond 5 miles from the residence.

A key finding is that access to non-centered jobs often has a larger association with VMT reduction than does access to jobs in sub-centers. Employment access is typically a short-distance phenomenon, more often statistically significant and with a larger magnitude (elasticity) for job access within five miles of a household's residence. The exception to these general findings occurs in Table 11, Model 11, for Orange County, where access to jobs in the 3rd through 46th sub-centers and beyond five miles from a household's residence has the largest elasticity.

Note that these two findings reinforce each other and point to employment access as a "short-distance" effect on VMT. Figure 17 and Figure 18 show the spatial distribution of the gravity variables for access to non-centered jobs that are less than five miles from households (Figure 17) and beyond five miles from households (Figure 18). In both cases, larger values (better access) are in the central part of the study area – not only in Los Angeles and Orange Counties but in the more urbanized and central portions of those counties. Note that the places with the best access to non-centered jobs are very central locations, and are at least visually proximate to the same places that have good access to the jobs in the largest and second-largest sub-centers. The fact that even non-centered jobs are concentrated in the urban core, and the fact that the largest magnitudes are for access variables limited to jobs within five miles of a household, both suggest that an overall strategy which focuses development near the center of the study region would be more successful in reducing VMT. The inland counties usually have weaker access to non-centered jobs (see Figure 17 and Figure 18), and in the inland counties improving access to non-centered jobs is only associated with VMT reduction when those jobs are within five miles of a household (Table 11, Model 12.) In net, placing jobs near residents, and residents near jobs, is a good strategy for VMT reduction in all parts of the Los Angeles CSA. As with previous research (e.g. Salon, 2013), our results suggest that improving employment access within five miles of a household is most likely to be associated with lower household VMT.

Deployment and Implementation

This research was largely intended to illuminate areas for research and policy consideration. We recommend the following steps in deploying the findings into practice:

- Future research should examine how refined, "near-residence" measures of job access can assist in metropolitan travel modeling. A key finding in this research is the importance of job accessibility within five miles of a household's residence when looking for associations between land use and VMT. We suggest that this information be disseminated to Metropolitan Planning Organizations (MPO) and state travel model groups to assist in their development and refinement of travel demand models.

- The policy simulations illuminate how VMT would change with changes in residence, assuming that the associations in this report of causal. While we caution that causality needs additional research, we believe that those associations can help inform broad land use planning efforts of the sort required under Senate Bill 375, e.g. We recommend that the results be disseminated to MPO planning staff for their consideration as one of many factors to consider in the land use planning process.

Appendix: Full Regression Tables on Models

Table 13: Regression Models for Accessibility to All Jobs

	All counties Model 1	Coastal counties Model 2	Inland counties Model 3
Accessibility to jobs - quadratic damping	-0.815***	-0.854***	-1.414*
<i>elasticity</i>	[-1.041,-0.588]	[-1.103,-0.606]	[-2.920,0.093]
Household vehicle holding	-0.249	-0.347	-0.140
	10.322***	11.084***	8.629***
	[0.512]	[0.579]	[1.030]
Household income			
less than \$ 10,000		(reference)	
\$10,000 to \$24,999	11.078***	11.672***	9.465*
	[2.416]	[2.702]	[4.960]
\$25,000 to \$34,999	17.502***	16.935***	17.416***
	[2.531]	[2.847]	[5.139]
\$35,000 to \$49,999	23.211***	24.742***	18.435***
	[2.438]	[2.735]	[4.975]
\$50,000 to \$74,999	29.729***	31.054***	25.559***
	[2.361]	[2.646]	[4.827]
\$75,000 to \$99,999	32.967***	33.005***	31.309***
	[2.410]	[2.704]	[4.927]
\$100,000 to \$149,999	35.167***	33.307***	38.189***
	[2.405]	[2.693]	[4.939]
\$150,000 to \$199,999	37.238***	37.490***	34.937***
	[2.658]	[2.943]	[5.624]
\$200,000 to \$249,999	40.996***	39.269***	44.299***
	[3.186]	[3.480]	[7.018]
\$250,000 or more	32.980***	32.068***	34.852***
	[3.140]	[3.398]	[7.195]
Household Size	5.312***	4.433***	7.197***
	[0.308]	[0.351]	[0.608]
Density (1k per sq mile)	-0.231***	-0.226***	0.034
	[0.070]	[0.068]	[0.284]
Intercept	-24.113***	-22.150***	-26.163***
	[2.378]	[2.753]	[4.867]
sigma	44.660***	41.388***	51.108***
	[0.318]	[0.355]	[0.655]
N	13475	9361	4114

95% confidence interval / standard error in brackets, * p<0.10, ** p<0.05, *** p<0.0

Table 14: Regression Models for Accessibility to Jobs Inside and Outside Employment Centers

	All counties Model 4	Coastal counties Model 5	Inland counties Model 6
Accessibility to jobs in the sub-centers - quadratic damping	-0.722*** [-0.975,-0.468]	-0.784*** [-1.037,-0.531]	-2.4 [-6.739,1.939]
<i>elasticity</i>	-0.111	-0.174	
Accessibility to jobs outside sub-centers - quadratic damping	-1.258*** [-1.843,-0.673]	-1.863*** [-2.623,-1.104]	-1.149 [-3.009,0.711]
<i>elasticity</i>	-0.191	-0.347	
Household vehicle holding	10.356*** [0.513]	11.138*** [0.579]	8.622*** [1.030]
Household income			
less than \$ 10,000		(reference)	
\$10,000 to \$24,999	11.119*** [2.415]	11.789*** [2.700]	9.438* [4.961]
\$25,000 to \$34,999	17.543*** [2.531]	17.056*** [2.844]	17.367*** [5.141]
\$35,000 to \$49,999	23.218*** [2.437]	24.715*** [2.732]	18.407*** [4.976]
\$50,000 to \$74,999	29.697*** [2.360]	30.876*** [2.644]	25.544*** [4.828]
\$75,000 to \$99,999	32.960*** [2.409]	32.775*** [2.702]	31.333*** [4.928]
\$100,000 to \$149,999	35.133*** [2.404]	32.953*** [2.694]	38.231*** [4.940]
\$150,000 to \$199,999	37.128*** [2.658]	36.890*** [2.949]	35.002*** [5.626]
\$200,000 to \$249,999	40.888*** [3.186]	38.667*** [3.484]	44.352*** [7.019]
\$250,000 or more	32.772*** [3.142]	31.219*** [3.409]	34.994*** [7.201]
Household Size	5.331*** [0.308]	4.506*** [0.352]	7.195*** [0.608]
Density (1k per sq mile)	-0.221*** [0.070]	-0.212*** [0.068]	0.013 [0.288]
Intercept	-23.202*** [2.443]	-18.928*** [2.986]	-26.169*** [4.867]
sigma	44.648*** [0.318]	41.355*** [0.354]	51.106*** [0.655]
N	13475	9361	4114

95% confidence interval / standard error in brackets, * p<0.10, ** p<0.05, *** p<0.01

Table 15: Regression Models for Accessibility to Jobs from Different Employment Centers

	All counties	Coastal counties	Inland counties
	Model 7	Model 8	Model 9
Accessibility to jobs in the largest sub-center - quadratic damping elasticity	-0.640*** [-0.911,-0.368] -0.047	-0.697*** [-0.960,-0.433] -0.076	-2.808 [-54.075,48.459]
Accessibility to jobs in the second-largest sub-center - quadratic damping elasticity	-0.926*** [-1.602,-0.251] -0.017	-1.128*** [-1.772,-0.485] -0.029	79.091*** [33.593,124.589] 0.140
Accessibility to jobs in the 3rd - 46th largest sub-center - quadratic damping elasticity	-1.196*** [-1.841,-0.552] -0.075	-1.418*** [-2.058,-0.778] -0.123	-2.266 [-6.754,2.222]
Accessibility to jobs outside sub-centers - quadratic damping elasticity	-1.041*** [-1.678,-0.405] -0.158	-1.640*** [-2.423,-0.858] -0.305	-3.146*** [-5.429,-0.862] -0.260
Household vehicle holding	10.356*** [0.513]	11.141*** [0.578]	8.573*** [1.028]
Household income		(reference)	
less than \$ 10,000			
\$10,000 to \$24,999	11.134*** [2.414]	11.818*** [2.698]	9.357* [4.951]
\$25,000 to \$34,999	17.564*** [2.530]	17.099*** [2.842]	17.360*** [5.130]
\$35,000 to \$49,999	23.222*** [2.436]	24.704*** [2.730]	18.130*** [4.967]
\$50,000 to \$74,999	29.747*** [2.359]	30.939*** [2.642]	25.159*** [4.824]
\$75,000 to \$99,999	33.019*** [2.409]	32.822*** [2.700]	30.920*** [4.930]
\$100,000 to \$149,999	35.202*** [2.404]	32.990*** [2.692]	37.705*** [4.952]
\$150,000 to \$199,999	37.226*** [2.658]	36.949*** [2.947]	34.782*** [5.647]
\$200,000 to \$249,999	40.951*** [3.186]	38.647*** [3.482]	43.998*** [7.034]
\$250,000 or more	32.858*** [3.143]	31.212*** [3.409]	35.311*** [7.228]
Household Size	5.310*** [0.308]	4.481*** [0.352]	7.055*** [0.607]
Density (1k per sq mile)	-0.231*** [0.070]	-0.226*** [0.068]	0.18 [0.292]

Table 15: Regression Models for Accessibility to Jobs from Different Employment Centers Continued

	All counties	Coastal counties	Inland counties
	Model 7	Model 8	Model 9
Intercept	-23.229***	-18.517***	-25.786***
	[2.442]	[2.989]	[4.865]
sigma	44.636***	41.330***	50.995***
	[0.318]	[0.354]	[0.654]
N	13475	9361	4114

95% confidence interval / standard error in brackets, * p<0.10, ** p<0.05, *** p<0.01

Table 16: Regression Models for Accessibility to Jobs from Different Employment Sub-Centers with 5-Mile Break Points

	All counties Model 10	Coastal counties Model 11	Inland counties Model 12	Coastal counties Model 13
Accessibility to jobs within 5 miles of residence and in the largest sub-center - quadratic damping <i>elasticity</i>	-0.567*** [-0.927,-0.208]	-0.433** [-0.782,-0.083]	0 [0.000,0.000]	-0.449** [-0.798,-0.100]
Accessibility to jobs beyond 5 miles of residence and in the largest sub-center - quadratic damping <i>elasticity</i>	-0.0309 [-4.448,2.201]	-0.0349 [-4.127,2.096]	-16.26 [-142.43,109.91]	
Accessibility to jobs within 5 miles of residence and in the second-largest sub-center - quadratic damping <i>elasticity</i>	-1.309*** [-2.125,-0.493]	-1.237*** [-1.997,-0.477]	0 [0.000,0.000]	-1.304*** [-1.996,-0.612]
Accessibility to jobs beyond 5 miles of residence and in the second-largest sub-center - quadratic damping <i>elasticity</i>	-0.015 [-6.583,4.437]	-0.021 [-8.630,2.230]	24.045 [-42.612,90.701]	
Accessibility to jobs within 5 miles of residence and in the 3rd - 46th largest sub-centers - quadratic damping <i>elasticity</i>	-1.026*** [-1.777,-0.275]	-1.167*** [-1.887,-0.446]	-2.212 [-6.848,2.423]	-1.200*** [-1.873,-0.526]
Accessibility to jobs beyond 5 miles of residence and in the 3rd - 46th largest sub-centers - quadratic damping <i>elasticity</i>	-0.0428 [-9.457** [-17.100,-1.814]	-0.0684 -12.257*** [-20.610,-3.905]	-7.797 [-78.111,62.516]	-9.992*** [-15.655,-4.330]
Accessibility to jobs within 5 miles of residence and outside sub-centers - quadratic damping <i>elasticity</i>	-0.196 -2.355*** [-3.500,-1.210]	-0.345 -1.628** [-2.903,-0.353]	-4.738*** [-7.440,-2.035]	-1.411** [-2.560,-0.262]
Accessibility to jobs beyond 5 miles of residence and outside sub-centers - quadratic damping <i>elasticity</i>	0.302 5.694*** [2.141,9.247]	-0.195 2.705 [-1.182,6.592]	-0.271 8.926 [-3.400,21.253]	
Household vehicle holding	10.304*** [0.512]	11.116*** [0.579]	8.497*** [1.027]	11.129*** [0.578]
Household income		(reference)		
less than \$ 10,000				
\$10,000 to \$24,999	11.050*** [2.412]	11.711*** [2.696]	9.226* [4.948]	11.749*** [2.697]
\$25,000 to \$34,999	17.450*** [2.527]	16.979*** [2.841]	17.127*** [5.127]	17.009*** [2.841]
\$35,000 to \$49,999	23.096***	24.549***	17.955***	24.542***

	[2.434]	[2.729]	[4.964]	[2.730]
\$50,000 to \$74,999	29.619***	30.819***	25.003***	30.766***
	[2.358]	[2.642]	[4.823]	[2.642]
\$75,000 to \$99,999	32.845***	32.639***	30.727***	32.588***
	[2.408]	[2.701]	[4.928]	[2.701]
\$100,000 to \$149,999	34.955***	32.809***	37.564***	32.737***
	[2.405]	[2.693]	[4.951]	[2.692]
\$150,000 to \$199,999	36.982***	36.786***	34.629***	36.661***
	[2.659]	[2.948]	[5.644]	[2.947]
\$200,000 to \$249,999	40.758***	38.666***	43.915***	38.425***
	[3.192]	[3.487]	[7.035]	[3.481]
\$250,000 or more	32.843***	31.463***	35.114***	31.230***
	[3.148]	[3.411]	[7.224]	[3.408]
Household Size	5.283***	4.472***	6.995***	4.504***
	[0.309]	[0.353]	[0.608]	[0.352]
Density (1k per sq mile)	-0.204***	-0.207***	0.248	-0.207***
	[0.071]	[0.069]	[0.299]	[0.069]
Intercept	-24.139***	-18.270***	-26.857***	-17.623***
	[2.456]	[3.051]	[4.893]	[2.976]
sigma	44.595***	41.303***	50.958***	41.311***
	[0.318]	[0.354]	[0.653]	[0.354]

95% confidence interval / standard error in brackets, * p<0.10, ** p<0.05, *** p<0.01

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