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Edited by Gregory K. Ingram and Yu-Hung Hong

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Land Use and Vehicle Miles of Travel in the Climate Change Debate: Getting Smarter Than Your Average Bear

Marlon G. Boarnet, Douglas Houston,
Gavin Ferguson, and Steven Spears

A common planning response to climate change has been to focus on the relationship between land use and travel behavior. The transportation sector was responsible for 27 percent of the greenhouse gas (GHG) emissions in the United States in 2008 (EPA 2010).[1] If cities were built at higher densities, with mixed land uses and alternatives to car travel, would that help reduce GHG emissions? That question has been hotly debated (Boarnet 2010; Moore,

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1. A more common estimate is that the transportation sector is responsible for about one-third of all U.S. GHG emissions. That estimate is from the years before 2008 and compares the transportation sector to net emissions (after carbon sinks) rather than to gross emissions (without sinks), which for 2008 puts the transportation sector at 27 percent of the total (EPA 2010).

Staley, and Poole 2010; Winkelman and Bishins 2010), yet amid that debate, a key issue has been overlooked.

Almost everything that we know about land use and travel behavior is derived from regional averages, typically from studies that analyze travel diary data for a metropolitan area or larger geographies. We know almost nothing about departures from metropolitan area averages. Are there places where the impact of land use on vehicle miles of travel (VMT) might be larger or smaller than the metropolitan average? Is the relationship between particular land use variables and VMT characterized by nonlinearities or thresholds? Both logic and the limited evidence we have suggest that the answer is "yes," but the question of nonlinearities, or thresholds, in the land use–VMT relationship has rarely been examined. Policy application necessarily requires an understanding not only of an average effect, but also of where limited resources and attention might be applied. This chapter is an attempt to move beyond broad averages, to search for thresholds in land use–VMT links, and to do so in a way that begins to illuminate the role for land use planning in the climate change debate.

In this chapter, we use exceptionally detailed travel diary data for the six-county Southern California Association of Governments (SCAG) region, covering the greater Los Angeles metropolitan area. Our primary methodological tool is a standard land use–travel behavior regression. We regress household VMT on a set of household sociodemographic variables and land use measures at the household's place of residence, but we estimate the regression for threshold values of key land use variables, to test for nonlinearities and interactions among these variables.[2] Overall, we find that access to regional employment has a nonlinear effect on VMT. Converting our regression results to elasticities, we find elasticities of VMT with respect to employment accessibility that are, in some cases, three to four times larger than corresponding elasticities in the literature, suggesting that the influence of land use can vary in ways largely overlooked by previous research.

Background: The Literature on Land Use and Travel Behavior

Scores of studies have focused on land use and travel behavior. For reviews of the literature, see Badoe and Miller (2000); Boarnet and Crane (2001, chap. 3);

2. The data provide information only on VMT, not on GHG emissions. We note that conditional on vehicle fleet composition, reductions in VMT will be associated with reductions in GHG emissions. There is a broader debate about whether GHG reduction should come from increases in vehicle fuel efficiency or from reductions in VMT. Policy will likely need both levers—high fleet fuel efficiency and measures that reduce the growth of VMT—partly because experts estimate that available increases in fuel efficiency will not be sufficient to meet GHG reduction goals, but more importantly because planning efforts that slow the growth of VMT have many cobenefits, including reductions in pollutants criteria and improvements in community quality of life.

Brownstone (2008); Crane (2000); Ewing and Cervero (2001); and Handy (2005). A recent National Research Council (NRC) report concluded that the elasticity of VMT with respect to population density is in the range of –0.05 to –0.12, and that accounting for the effect of changing multiple land use variables together, the impact of compact development on VMT might imply an elasticity on the order of –0.25 (NRC 2009). That report, while stating that the data sources, and hence the scientific evidence, were at times thinner than would be preferred, concluded that both logic and available evidence suggest that the relationship is at least in part causal, implying that increases in density would reduce VMT. Translating the density-VMT relationship into reductions in GHG emissions, the report estimated that more compact development could reduce GHG emissions, below a baseline trend, by an amount in the range of less than 1 percent to approximately 11 percent by 2050.

Viewed more broadly, the link between land use and travel behavior is at once obvious and an exceptionally slippery topic of empirical study. Nearly 60 years ago, Mitchell and Rapkin (1954) wrote one of the earliest tomes on travel demand modeling, *Urban Traffic: A Function of Land Use*. The title reflects both the obvious nature of that link and a viewpoint that underpins travel demand modeling to this day. Yet viewing travel as a behavioral response complicates matters substantially. People can change when and how they travel, and by choosing their place of residence, job location, and activity locations, persons can also choose their trip origins and destinations. That behavioral reality, spanning several markets all characterized by imperfect data, combined with few opportunities to observe natural experiments, complicates the empirical literature on land use and travel behavior.

In the past two decades, a standard approach to studying land use and travel behavior has developed. Measures of individual or household travel, typically from a travel diary, are regressed on sociodemographic variables (e.g., income, age, number of children, and employment status) and land use variables typically measured near the person's or household's residence. The use of data for individuals or households avoids aggregation problems and potentially allows better causal influence. Recent high-quality applications of this approach include Bento et al. (2005); Bhat and Guo (2007); Brownstone and Golob (2009); and Fang (2008). Although there is a common regression approach to this topic, several methodological issues have been debated. The most important ones are discussed in this section.

MEASURING LAND USE

The NRC's elasticity estimate focused on density, because that is the most common variable used in the literature (NRC 2009). Yet density is a proxy—and likely often a weak one—for a broad range of land use variables. Generally, land use is measured according to what are called the "D variables" or the "5 D's"—density (of population); diversity (land use mix); design (the character of the street network and, for some studies, the quality of the pedestrian environment); access to destinations (often measured as access to regional job centers or employment); and distance from transit, or, more completely, access to and characteristics of the regional transportation network. Some of these variables are very local, often measured for neighborhoods that approximate walking distance in size, typically a one-quarter- or one-half-mile radius area. Population density, land use mix, and the character of the street network are usually measured for localized neighborhoods and are intended to reflect some of the neighborhood-scale ideas associated with Smart Growth or, to phrase things more neutrally, compact development. Other variables—access to regional employment and characteristics of and distance from the transportation network—describe geographies at the scale of the metropolitan area. For a discussion of local and regional access and these different geographies, see Handy (1993).

RESIDENTIAL SELECTION

Economic actors might choose their locations in part based on how they wish to travel or, for firms, how people can travel to them. Households that wish to walk might choose to live in a walking-oriented neighborhood. Firms will locate based on transportation accessibility. The literature on land use and travel, being almost exclusively focused on household travel due to data constraints, has focused on how people locate, called "residential selection."

The idea that households might locate based on how they wish to travel was first suggested by Boarnet and Sarmiento (1998), who modeled this as an endogeneity problem, using instrumental variables as a correction. Since then, several studies have modeled residential selection, using a variety of techniques. Cao, Mokhtarian, and Handy (2009) reviewed the literature on residential selection, finding that virtually every study that attempted to control for the possible endogeneity of household location found that econometric controls did not change the sign or significance of the land use–travel behavior association. In some cases, the magnitude of the land use–travel effect was attenuated after controlling econometrically for residential selection. The association between land use and travel appears to be partly causal and partly people sorting (or choosing) residential locations that match their travel preference.

The review by Cao, Mokhtarian, and Handy (2009) treats residential selection as an econometric problem, as is typical of the literature. But addressing only whether selection occurs or not and how to correct for residential selection in a regression ignores the question of whether selection should or should not be considered part of the policy impact.

The selection question is motivated in part by econometric studies of labor markets. A good analogy for the labor economics perspective is job training programs. Suppose that a voluntary job training and job search program is offered to people formerly employed at a mythical factory that recently closed. Presumably, the voluntary program will attract the most motivated, and possibly the more highly skilled, former employees. Graduates of the training program might find jobs more quickly, but one would want to adjust for the selection of people into training. If, in the extreme case, the training program imparts no skills, through selection participants could still do better in their job search than nonparticipants. In that extreme case, the entire "program effect" is selection, rather than the effect of the training program itself, and presumably the training participants would have found the same jobs had there never been a training program.

Suppose instead that there is a distribution of people, the most motivated of whom will benefit from job training (possibly because their motivation will cause them to better leverage the training into better jobs), and the least motivated of whom will not benefit from job training. All participants select into the training program (maybe the program was so effectively marketed that even the unmotivated chose to participate). If there are other preexisting and perfectly suitable training or education options, the new training program will have no impact on labor market outcomes—the motivated will obtain training elsewhere, and all the new program will do is enroll less motivated people who will not benefit from the training. If, however, no other training programs exist, our mythical factory's job training program will improve labor market outcomes. In a case where a good (the job training program in this example) produces an impact for at least some who select it and the good is in short supply, such that all who could benefit cannot consume (i.e., there are no other training programs), the supply of the good itself can be considered part of the policy impact.

Which analogy better fits compact development, or Smart Growth? Is compact development an adequately supplied service, providing no intrinsic change in travel behavior, such that selection is not part of the policy effect? Or is compact development a desired (and desirable) but undersupplied good, such that selection could legitimately be the whole of the policy effect? More important, if there is a distribution of travel preferences, how does the supply of neighborhoods match the demand for travel and hence neighborhood type? Levine (2006) argues that compact development is undersupplied and that selection should be viewed as a legitimate part of any land use–travel impact.

A full analysis would be complex and, to our knowledge, has never been attempted. One would have to formally model developer behavior and possibly government regulations that influence the supply of neighborhoods, as well as travel behavior, and the interactions between those variables via land use change.[3]

3. An alternative would be to examine the land use–travel behavior relationship in a metropolitan area with an abundant supply of compact development, hypothesizing that in such locations, the marginal effect of land use on travel is not due to people who desire compact neighborhoods sorting into such neighborhoods, but instead is due to a direct effect of land use on travel. To the best of our knowledge, such a method for illuminating the residential selection question has not been tried. Note, though, that "abundant supply" would have to be measured relative to consumer preferences, complicating the research design, as simply looking for locations with a large amount of compact development would not necessarily imply "abundance" if those places also had high demand for compact development. Relatedly, it is possible that some people might migrate across metropolitan areas based in part on characteristics

This would go somewhat beyond trying to econometrically control for residential selection to uncover an effect absent selection, as those methods do not address the question of whether selection is or is not part of the policy impact. So while residential selection has become possibly the central methodological issue in this literature, the approach has been narrow in ways not broadly appreciated. Yet our concern here is not broadening the argument beyond econometric corrections for residential selection, but putting on the table an equally important methodological concern that has received almost no attention.

REGIONAL AVERAGE IMPACTS AND DEPARTURES FROM REGIONAL AVERAGES

Regression analyses of land use and travel give coefficients that represent an average effect for the data set. There are many such studies—enough that the literature has settled on a common range for various land use variables. Studies of individual travel diary data that correct for residential selection suggest that the elasticity of VMT with respect to population density is in a range from −0.05 to −0.12 (Bento et al. 2005; Brownstone and Golob 2009; Del Valle and Niemeier 2010; Fang 2008; NRC 2009).[4] Studies give an elasticity of VMT with respect to land use mix in a range from −0.01 to −0.06 (Bento et al. 2005; Chapman and Frank 2004; Frank and Engelke 2005; Kockelman 1997; Pushkar, Hollingworth, and Miller 2000). Regional accessibility to jobs has a larger VMT elasticity—typically in the range of −0.15 to −0.31 (Ewing and Cervero 2010, table A-4). Meta-analyses give results that are typical of these individual studies. Two meta-analyses by Ewing and Cervero (2001, 2010) found elasticities of VMT with respect to population density and land use mix in the range of −0.04 to −0.09 and an elasticity of VMT with respect to regional access to jobs in the range of −0.20 to −0.22, leading to the general conclusion that the regional (or metropolitan-wide) distribution of employment has a larger magnitude effect on VMT than do neighborhood-scale land use variables.[5]

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that include the supply of compact development. While there is no good formal evidence for migration based on a metropolitan area's compactness, commentators have speculated on such possibilities (*Economist* 2010). All of these issues illuminate the need for a more structural approach to questions of land use, travel, and residential selection, but such efforts are beyond the scope of the study presented here.

4. Del Valle and Niemeier (2010) found an elasticity of VMT with respect to residential density equal to −0.19. That paper was not available at the time of the NRC (2009) study, and so the range typically identified by NRC (2009) and similar efforts is −0.05 to −0.12.

5. Note that this conclusion overlooks some complexity. Ewing and Cervero (2010), in their meta-analysis, found that the VMT elasticity of the street network—measured by the density of street intersections and the percentage of intersections that are four-way—is −0.12 and the elasticity of walking with respect to intersection density is 0.39. But looking across a range of variables and impacts, the regional employment elasticity of VMT is typically larger than elasticities for neighborhood-level land use variables.

Although an average effect for a metropolitan area is one piece of the policy puzzle, knowing whether and how the size of the effect varies across different land use contexts is just as important. The literature gives little information about departures from regional (or metropolitan area) average effects, but some small-area studies suggest that such departures can be important. For example, Boarnet et al. (2011) found substantial travel behavior variation within their relatively small study neighborhoods. For one neighborhood, controlling for household characteristics, residents within one-quarter mile of a commercial concentration averaged five times more walking trips and 25 percent fewer driving trips than those in the rest of the same neighborhood, all of whom were within a mile of the commercial concentration.[6] Moving from that specific example to the general, where might land use policy achieve more, or less, bang for the compact development buck?

California's Senate Bill (SB) 375 moves this question to the fore of metropolitan planning. SB 375 requires that the state's 18 metropolitan planning organizations (MPOs) develop sustainable community strategies (SCSs), which will demonstrate how each MPO's regional transportation plan and affordable housing strategy combine to meet GHG emission reduction targets established by the California Air Resources Board. In the SCAG region—the largest MPO in the state and the nation—this requires an SCS that is, in part, an amalgamation of the transportation investment and general plan decisions of 189 cities and six counties. Development patterns in the SCAG region range from the high-rise canyons of the highly urban Wilshire corridor to exurban commuter suburbs separated from job centers by commutes of an hour or more. Should attention be focused on inner locations with urban character, or would policies targeted toward the exurban fringe have a larger impact? Although it is obvious that land use–transportation plans should be sensitive to local context, beyond good planning intuition there is little in the way of analytics that can help refine and apply that insight. SCAG has conducted a visioning process that identifies areas for targeted infill development (called Compass 2% Strategy Opportunity Areas),[7] but that identification was largely based on access to bus or rail transit, rather than the larger menu of land use variables used in this study.

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6. Using data in Boarnet et al. (2011), the results from the neighborhood in question imply an approximate 25 percent decrease in car trip generation rates across two locations where housing unit density differs by about 50 percent. Although density was not included directly in the regression, an approximate 50 percent increase in density associated with an approximate 25 percent reduction in car trip generation rates implies a larger elasticity than is typical in the literature. As a comparison, trip generation elasticities with respect to population density in the more regional-level studies reviewed by Ewing and Cervero (2001) were never larger than 0.15 in magnitude.

7. "Compass" is not an acronym. The term was used to indicate a direction or a charting of a course, presumably to communicate the future-oriented nature of the growth vision plan. See SCAG (2004) and http://www.compassblueprint.org/opportunityareas for more information.

Data

VMT data are derived from the SCAG 2001 regional travel survey (NuStats 2003). The survey was conducted in the spring and fall of 2001 and the spring of 2002. The survey included a travel diary completed by 16,939 households in the six-county region (Los Angeles, Orange, Riverside, San Bernardino, Ventura, and Imperial). Most of the households kept the diary for one day, but 2,416 households completed a two-day diary that included one weekend day. Start days were staggered throughout the week.

Participants recorded all trip origin and destination locations for all household members, plus travel mode, trip purpose, and time of day. Trip origins and destinations were geocoded by SCAG and their survey contractor, NuStats. We used the geocoded trip origins and destinations to obtain trip distances and total household VMT for the diary period.

In February 2010, we routed all trips over a street and highway network using MapQuest, choosing the minimum travel time option. The routing method is internal to MapQuest, but we experimented with two other routing tools, CloudMade and Google Maps, and found little difference in overall VMT calculations. In theory, the fact that the street and highway network was for early 2010 rather than for the survey year (2001–2002) could create errors due to road and street construction in the intervening years. In practice, however, we doubt that this is much of an issue, as no new streets or highways were constructed during the intervening nine years in most locations that were covered by the survey. We examined several routed trips visually and found that the routing method was reasonable and gave the expected routes.

As a further check, we compared our household VMT to an estimate of household VMT calculated by SCAG using a 2003 road network.[8] SCAG's VMT calculation was available for approximately 70 percent of the households in the data set, or 10,630 households. For each of those households, we formed the difference between household VMT using the 2003 SCAG calculation and household VMT using the 2010 MapQuest routing. The mean and median differences in household VMT for the two routing methods were –1.45 and 0.67 miles, respectively.[9] Differences are distributed roughly evenly across both negative and positive values, suggesting no obvious bias from either source. The middle 80 percent of the differences for the two routing methods (using 2003 or 2010 street maps) are approximately ±7 miles. After visual inspection of households with

8. SCAG's VMT data were available only at the household level, not by individual trip, preventing us from being able to recalculate VMT with different assumptions or decompose travel by different sets of trips. For that reason, we believe it is preferable to use SCAG as a quality check for our routing method, since our VMT data are disaggregated to the trip level and so allow more detailed future analysis.

9. For context, the mean household VMT for both methods was approximately 48 miles.

large differences, either positive or negative, we concluded that any differences appear unrelated to the year of the road network and are more likely related to differing decisions about whether to include out-of-region travel. We prefer the inclusion criteria for trips that we developed.

In our analysis, trips were discarded if the survey variable *spdflag* indicated respondent error (*spdflag* = 1) or unresolved speed violation (*spdflag* = 5). The *spdflag* variable was developed by SCAG to indicate trips that could not be routed over the network. Those trips often resulted from errors in the respondent's identification of trip origin or destination location, or cases where the implied travel speed was much faster than allowed travel speeds, as identified in SCAG's quality check of the data. Some of these erroneous trips were very long—in some cases several hundred miles—but corresponded to short travel times. We included trips that were outside the six-county metropolitan area, as our interest was in total VMT, subject to the condition that the *spdflag* variable did not indicate respondent errors. Lastly, we took care to avoid counting the same trip more than once when multiple household members traveled in the same vehicle.

The sociodemographic variables we used came from the travel diary. The land use variables were obtained from geographic information systems (GIS), using the geocoded residential location of each travel diary household. Data included the 2000 census, SCAG data on land use categories and for number of jobs by census tract for 2000, and rail and bus routes. Conceptually the land use variables are in three groups:

- Variables that measure neighborhood-level characteristics: population density within a one-quarter-mile radius of the household; fraction of land that is in commercial use within one-quarter mile of the household; fraction of land that is in medium- or high-density residential use within one-quarter mile of the household; total number of street intersections within one-half mile of the household (a measure of block size); and fraction of street intersections that are four-way (a measure of grid orientedness of the street network) within one-half mile of the household.
- Variables that measure access to jobs throughout the metropolitan area (regional access to jobs): distance from the central business district (Los Angeles City Hall) and a gravity variable that sums census tract employment damped by straight-line distance (in meters) from the household's residence to the centroid of each census tract.
- Variables that measure access to the transportation network: distance from the nearest freeway on-ramp; dummy variable indicating whether the household is within one-quarter mile or one-half mile of a rail transit station; dummy variable indicating whether the household is within one-half mile of a bus station; dummy variable indicating whether the household is within one-half mile of an express bus station; dummy variable indicating whether the household is within one-half mile of a rapid bus station.

In addition, a dummy variable indicating whether the household is within a Compass 2% Strategy Opportunity Area was used in the regression. The Compass areas were developed as part of a planning exercise that culminated in the SCAG Compass Blueprint plan in 2004. These areas were judged by SCAG to be good targets for infill development and were chosen based on access to employment or activity centers, access to rail or bus transit, and infill development opportunities.

Collectively, these land use variables provide a comprehensive treatment of the typical "5D" approach to land use measurement. Descriptive statistics for the land use variables are shown in appendix A, which includes all households with a full set of sociodemographic variables.

VMT in the SCAG Region: Descriptive Results

Table 7.1 gives descriptive statistics for VMT in the full sample for the SCAG travel diary. There are 118 households for which VMT could not be derived, and another 3,220 households (19 percent of the sample) with zero VMT during the diary period. That proportion of zero VMT households is not uncommon in one-day travel diary surveys.

Table 7.2 shows the distribution of total VMT for all trips in the diary by trip length. For comparison, two other data sets—the 2001 National Household Travel Survey (NHTS) Los Angeles consolidated metropolitan statistical area (CMSA) subsample and the NHTS national sample—were analyzed. Note first

Table 7.1
Household VMT

	VMT		
	Total	**Weekday**	**Weekend**
Mean	47.81	42.89	34.51
Std. dev.	77.52	67.37	69.37
10th percentile	0.00	0.00	0.00
25th percentile	4.75	4.09	0.00
75th percentile	62.11	56.81	41.78
90th percentile	116.32	104.49	91.26
Number of households	16,939	16,939	2,414

Note: One-day diary for 14,523 households; two-day diary for 2,416 households. "Total" is for the full diary period, either one day or two days. Households that completed a two-day diary did so for one weekday and one weekend day, allowing VMT descriptive statistics for weekdays (from the full sample) and weekend days (from the two-day diaries).
Source: SCAG travel diary, SCAG 2001 regional travel survey (NuStats 2003); authors' calculations.

Table 7.2
Household VMT, by Trip Length

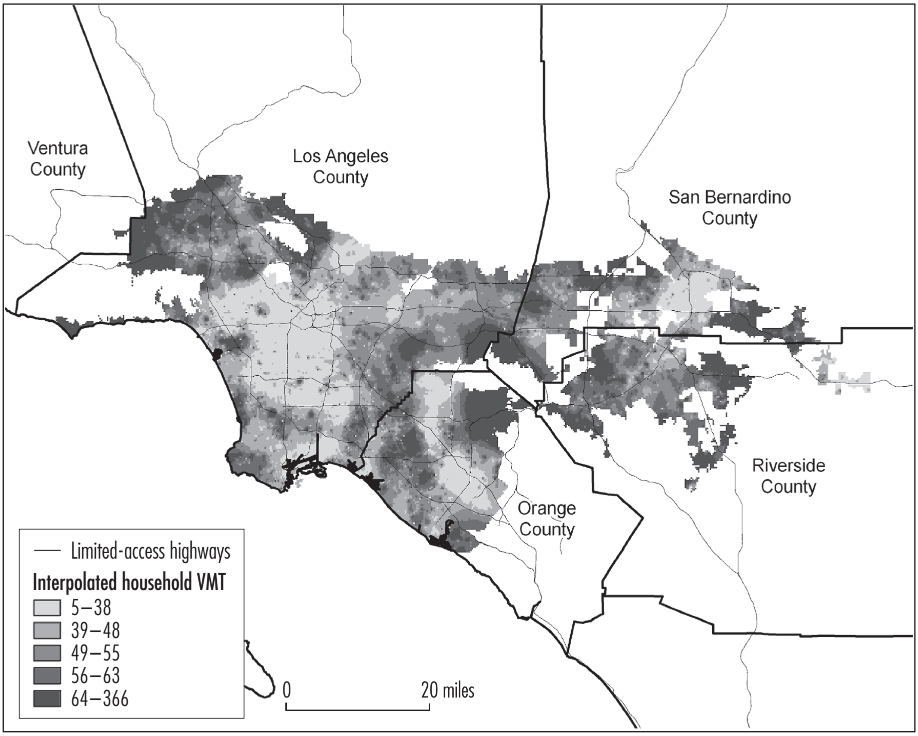
	SCAG LA		NHTS LA CMSA		NHTS National	
Trip Length (miles)	**Percentage of VMT**	**Cumulative Percentage**	**Percentage of VMT**	**Cumulative Percentage**	**Percentage of VMT**	**Cumulative Percentage**
0–2	2.96	2.96	1.72	1.72	1.57	1.57
2–4	5.75	8.71	5.12	6.84	5.48	7.06
4–6	5.62	14.33	7.35	14.20	6.48	13.54
6–8	5.14	19.46	5.92	20.12	5.70	19.24
8–10	4.73	24.20	4.20	24.32	4.70	23.94
10–20	20.87	45.07	21.91	46.23	21.80	45.75
20–30	14.20	59.27	16.92	63.16	13.78	59.53
30–50	16.04	75.30	14.86	78.02	14.16	73.68
50–100	15.19	90.49	15.02	93.04	11.05	84.73
100–200	6.56	97.05	4.10	97.14	7.03	91.76
>200	2.95	100.00	2.86	100.00	8.24	100.00

SCAG LA = Southern California Association of Governments, greater Los Angeles metropolitan area regional travel survey; NHTS LA CMSA = National Household Travel Survey, Los Angeles consolidated metropolitan statistical area sample; NHTS National = National Household Travel Survey, national sample.
Source: SCAG travel diary, SCAG 2001 regional travel survey (NuStats 2003); NHTS *(2001 National Household Travel Survey User's Guide)*; authors' calculations.

that the cumulative distributions are similar for all three data sources, providing some assurance that any inaccuracy in network routing is, in the aggregate, likely small. More important, table 7.2 illustrates the significance of long trips in total VMT. Both the NHTS and SCAG diary data show that trips of 30 miles or longer account for approximately 40 percent of all VMT in the Los Angeles region. This suggests that land use policies that influence short trips may be less effective than those that influence long trips if the goal is reducing GHG emissions. Note, though, that California's SB 375 is primarily a regional planning tool, targeting transportation infrastructure and affordable housing, although the specific implementation has yet to unfold. Also note that table 7.2 suggests that attention to regional accessibility may be more important than attention to neighborhood-level land use measures, although for completeness we include both in our analysis.

Figure 7.1 shows survey household VMT, smoothed by interpolating between household locations, for the 11,218 survey households in the two largest urbanized areas (Los Angeles–Long Beach–Santa Ana and Riverside–San Bernardino) in the SCAG region. A spatial pattern is clearly evident. The largest area

Figure 7.1
Interpolated VMT Quintiles: Households in the Los Angeles–Long Beach–Santa Ana and Riverside–San Bernardino Census Urbanized Areas



Source: Authors' calculations from SCAG 2001 travel diary (NuStats 2003).

of light gray (the lowest VMT quintile) is the central and south-central part of the city of Los Angeles, with another large light gray area near Santa Ana and Irvine in central Orange County. Parts of both places have exceptional job accessibility. Studies of employment subcenters in the SCAG region (Funderburg and Boarnet 2008; Redfearn 2007) suggest that downtown Los Angeles and central Orange County are among the two largest and most economically complex job centers in the metropolitan area. Income is an important explanatory factor, as south-central Los Angeles and Santa Ana are lower-income areas, but the locations of low VMT extend into high-income, job-accessible locations such as Irvine and Santa Monica. The dark gray areas on the fringe of the region suggest that, as expected, households in more exurban locations have higher VMT.

Table 7.3 shows VMT by county. The inner counties, Los Angeles and Orange, have lower household VMT. Table 7.4 shows VMT for households inside and outside what would later be designated the Compass 2% Strategy Opportunity Areas. Households inside that area had lower VMT than households outside the areas. Table 7.5 splits the sample based on distance from a rail or bus stop

Table 7.3
Household VMT, by County

	Number of Observations	Mean	Std. Dev.
Imperial	897	35.36	66.50
Los Angeles	7,222	44.10	74.14
Orange	2,304	48.32	77.53
Riverside	2,324	54.47	74.63
San Bernardino	2,155	57.57	91.95
Ventura	1,919	51.13	80.34

Source: SCAG travel diary, SCAG 2001 regional travel survey (NuStats 2003); authors' calculations.

Table 7.4
Household VMT, Inside and Outside Compass 2% Strategy Opportunity Areas

	Inside	Outside
Mean	36.79	52.99
Std. dev.	61.54	83.17
Number of observations	5,005	11,816
t-statistic		13.98

Source: SCAG travel diary, SCAG 2001 regional travel survey (NuStats 2003); authors' calculations.

Table 7.5
Household VMT, Split at One-Quarter Mile from Rail or Bus Station

	<¼ Mile from Rail	>¼ Mile from Rail	<¼ Mile from Bus	>¼ Mile from Bus
Mean	21.05	48.39	44.58	55.18
Std. dev.	32.63	77.94	77.31	78.04
Number of observations	137	16,684	11,122	5,699
t-statistic		9.59		8.36

Source: SCAG travel diary, SCAG 2001 regional travel survey (NuStats 2003); authors' calculations.

Table 7.6
Household VMT, Split at One-Half Mile from Rail, Express Bus, or Rapid Bus Station

	<½ Mile from Rail	>½ Mile from Rail	<½ Mile from Express Bus	>½ Mile from Express Bus	<½ Mile from Rapid Bus	>½ Mile from Rapid Bus
Mean	25.49	48.98	42.23	50.18	32.90	50.51
Std. dev.	46.93	78.48	64.86	81.51	63.17	79.45
Number of observations	583	16,238	4,250	12,571	2,233	14,588
t-statistic		11.53		6.46		11.82

Source: SCAG travel diary, SCAG 2001 regional travel survey (NuStats 2003); authors' calculations.

(more or less than one-quarter mile). Table 7.6 splits the sample according to distance from a rail, express bus, or rapid bus stop (more or less than one-half mile). All the VMT differences in tables 7.4–7.6 are statistically significant using two-sample t-tests with unequal variances across groups. (A small number of households had missing VMT data, so the sample in tables 7.4–7.6 includes 16,821 households.)

Methodology

We used a standard land use–travel behavior regression to examine how VMT is related to land use:

$$VMT_i = \mathbf{SD}_i\beta_1 + \mathbf{LU}_i\beta_2 + u_i \tag{1}$$

where VMT = household vehicle miles of travel during the travel diary period (one or two days);
SD = a row vector of sociodemographic variables for the household or the primary respondent in the household;
LU = a row vector of land use variables measured at the household's place of residence;
u = regression error term;
i indexes households; and
β_1 and β_2 are column vectors of parameters, with one including a constant.

A fairly extensive set of sociodemographic variables is available from the travel survey. These variables are shown in appendix A, with descriptive statistics for observations for which all sociodemographic variables are available. The sociodemographic variables compare favorably to the most extensive sets of variables used in the literature (e.g., Bhat and Guo 2007). Note that while we make no formal claims, Brownstone (2008) has suggested that including an extensive set of sociodemographic variables in the travel behavior regression might be sufficient to control for residential selection.

The literature has argued that land use variables should be divided into two geographic scales—(1) localized, neighborhood-scale measures of development patterns; and (2) overall measures of metropolitan settlement patterns (Handy 1993). Much of the literature has been silent on this distinction, but the evidence that is available suggests that this local/regional distinction is important (Boarnet and Sarmiento 1998; Ewing and Cervero 2001, 2010). The two levels of geography correspond to different policy agendas. The neighborhood scale corresponds to discussions of Smart Growth or compact development, while the regional scale links more closely to metropolitan growth patterns, including research on the pattern of employment centering and centralization within urban areas (Giuliano, Agarwal, and Redfearn 2008).

We believe that the local/regional distinction is vital, and we chose one variable as a key measure of each of the local and regional land use patterns. Population density within one-quarter mile of the place of residence is the local land use measure, and employment accessibility (the gravity variable with linear straight-line distance damping) is the regional accessibility measure. We examine thresholds and interactions for these two variables—thresholds in local accessibility, thresholds in regional accessibility, and interactions between local and regional accessibility. We chose population density and employment accessibility because those two variables are, respectively, the most common measures of local and regional accessibility in the literature on land use and travel, so a focus on thresholds in those two variables more easily allows comparisons of our results to the literature. In a fully generalized approach, one could run a second-order approximation of a trans-log functional form for the land use variables, using linear and quadratic terms and interactions for all those variables. We did not pursue that approach because such specifications become difficult to interpret in cases like ours, with a large number of variables, and at this initial exploratory stage the simplification of examining thresholds and interactions in two variables has benefits in suggesting patterns and possible directions for future research.

The question of thresholds was examined three decades ago by Pushkarev and Zupan (1977), who studied population density thresholds and transit ridership. Since then, this question has been overlooked, leaving the recent land use–travel literature to statements of average effects for data sets that typically cover metropolitan areas or larger geographies.

Most of the analysis in the next section examines questions of thresholds in population density and employment accessibility, or interactions between the two. Yet we also explore thresholds for transit access and highway access. We examined VMT across threshold distances of a mile or less to transit and 10 miles to a freeway, as exploratory analyses suggested that those were key breakpoints in the data.

Regression Analysis and Results

REGRESSION SPECIFICATIONS

We used two regression approaches to examine the question of nonlinearities. In the first (and simpler) approach, we stratified the full sample into quintiles by population density and employment accessibility, then estimated the full regression shown in equation (1) on the households in each quintile.[10] This entailed two sets of regressions, first running the regression in equation (1) on the subsamples of households in the five different population density quintiles, then running the regression in equation (1) on the subsamples of households in the five different employment accessibility quintiles. We call this the "stratified sample" approach.

As a second specification, we developed spline variables for population density and employment accessibility to implement a piecewise regression approach, as described in Pindyck and Rubinfeld (1981). Specifically, we estimated the regression shown below, which we call the "spline regression" approach.

$$VMT = X\gamma + \sum_{q=1}^{5} \alpha_q PD^q + \sum_{q=1}^{5} \beta_q EA^q + u \tag{2}$$

where X combines the **SD** and **LU** matrices from equation (1), without the variables for population density (denoted PD) and employment accessibility (denoted EA).

The five spline variables EA^q are defined for each quintile $q \in [1,5]$:

$EA^q = 0$ if EA_i is below quintile q
$EA^q = (EA_i - EA_{q-1})$ if EA_i is within quintile q
$EA^q = (EA_q - EA_{q-1})$ if EA_i is above quintile q

where EA_i is the EA value for each household;

EA_q is the highest value for EA_i within each quintile q;
EA_{q-1} is the highest value for EA_i in the previous quintile; and
$EA_{q-1} = 0$ for the first quintile, $q = 1$.

10. The quintiles are defined relative to the 2001 SCAG household travel survey, so the population density and employment accessibility quintiles represent the distribution of SCAG survey households, which will depart from the underlying geography of the SCAG region to the extent that the 2001 survey sampled households nonuniformly across density or employment access. As a sensitivity test, it would be sensible to examine other groupings, such as deciles, both to better illuminate nonlinearities in the impacts of land use variables and to test whether the results obtained here are sensitive to the number of groups. Due to time constraints, we do not examine other groupings in this chapter, but we believe such sensitivity tests are an important question for future research.

Hence, $EA^1 = EA$ for each household in quintile 1 and the maximum value of *EA* in quintile 1 for all households in higher quintiles; $EA^2 = 0$ for households in quintile 1, the difference between EA_i and the upper bound of *EA* in quintile 1 for households in quintile 2, and the difference between the maximum and minimum values of *EA* in quintile 2 for households in quintiles higher than the second; and so on. The spline variables for *PD* are defined in the same way.[11]

The regression in equation (2) is a special case of a spline function, allowing the estimated coefficients to vary across the quintiles while maintaining the continuity of the relationship between *VMT* and both *PD* and *EA* at the quintile breakpoints. The regression in equation (2) also has more degrees of freedom, using all the households rather than running the regression separately on each quintile, as in the stratified sample approach. Yet the regression in equation (2) does not allow interaction effects between *PD* and *EA*, which can be more easily examined in the stratified sample approach.[12] Results from both approaches are reported here.

MARGINAL EFFECTS AND ELASTICITIES

It has become common to use elasticities to quantify the effect of land use variables on travel (Ewing and Cervero 2010; Tal, Handy, and Boarnet 2010). The elasticity of *VMT* with respect to *PD* is $\frac{\partial VMT}{\partial PD} \times \frac{PD}{VMT}$, and the elasticity of *VMT* with respect to *EA* is $\frac{\partial VMT}{\partial EA} \times \frac{EA}{VMT}$. For linear regression specifications, if the slope ($\frac{\partial VMT}{\partial PD}$ or $\frac{\partial VMT}{\partial EA}$) is constant, the elasticity will change as PD/VMT or EA/VMT changes. Stated more generally, elasticities vary for linear relationships as one moves along the line. For that reason, we examine both the marginal effects, $\partial VMT/\partial PD$ and $\partial VMT/\partial EA$, and the elasticities to assess whether changes in elasticities across the quintiles are due more to changes in marginal effects or to changes in the values for *PD*, *EA*, and *VMT*.

Because *VMT* for our sample of households is left-censored, we used Tobit regression for both the stratified sample and spline regression approaches. Because Tobit regression is nonlinear, estimating elasticities at sample means (either for the full sample or at means within quintiles) can be misleading (Brownstone 2008). Both terms in the elasticity—the marginal effects, $\partial VMT/\partial PD$ and $\partial VMT/\partial EA$, and the ratios, PD/VMT and EA/VMT—vary for each household. We calculated

11. Because we used Tobit regression, the coefficients estimated in equations (1) and (2) show the relationship between the independent variables and the latent variable for *VMT*, rather than observed *VMT*. This is discussed later in this section.

12. It is possible to interact the spline variables with each other, but that creates 25 possible pairs of interactions, which do not reveal insights beyond what can be obtained from the stratified sample approach and so are not reported here.

the marginal effect and elasticity for each household, then averaged those marginal effects and elasticities for each quintile to obtain average marginal effects and elasticities within quintiles. The marginal effect for the stratified sample approach is as follows:[13]

$$(3) \qquad me_i = \beta_k \Phi\left(\frac{X_i \gamma}{\sigma}\right) = \frac{\partial E[VMT_i \mid X_i]}{\partial X_k}$$

where Φ = the cumulative normal probability distribution;
X = the full vector of independent variables in equation (1);
γ = the coefficients in vectors β_1 and β_2 in equation (1);
σ = standard error of the regression;
X_k = the land use variable, *PD* or *EA*;
β_k = coefficient on the land use variable; and
i = indexes households.

Note that the expression for me_i is listed as the partial derivative of *VMT* with respect to the land use variable. The expression for me_i in equation (3), and the analogous expression for me_i for spline regressions given in equation (4), give marginal effects of the land use variables on *VMT*, including the effect on those households with zero *VMT*—in other words, the marginal effect for the full sample used in the regressions.

Within each quintile, the average marginal effect and elasticity were then calculated as the average of the household values within that quintile:

$$me_q = \frac{1}{N_q} \sum_{i=1}^{N_q} me_i$$

$$elasticity_q = \frac{1}{N_q} \sum_{i=1}^{N_q} me_i \frac{lu_i}{E[VMT_i \mid X_i]}$$

where me = marginal effect;
q = indexes quintiles;
N_q = number of households in quintile q;
lu_i = land use variable (*PD* or *EA*) for household i; and
VMT_i = *VMT* for household i.

13. This is equivalent to the regression coefficient on the land use variable, *PD* or *EA*, multiplied by the probability that household *i* has nonzero *VMT* (Johnston and DiNardo 1997, 437).

For the spline regression, the marginal effect is shown as follows:

$$(4) \qquad me_i = \beta_k \Phi \left(\frac{X_i^- \gamma + \sum_{j=1}^{5} \beta_j lu_j}{\sigma} \right) = \frac{\partial E[VMT_i \mid X_i^-, lu_j]}{\partial lu_j}$$

where X_i^- = the set of independent variables in equation (1) less the five spline variables for the land use variable in question (*PD* or *EA*);

lu = *PD* or *EA*;

$\sum_{j=1}^{5} \beta_j lu_j$ = the sum of the five quintile variables multiplied by coefficients for the household *i*;

and as before,

Φ = the cumulative normal probability distribution;

β_k = the coefficient on the land use variable for the quintile of *PD* or *EA* that the household is in; and

σ = the standard error of the regression.

As before, within each quintile the marginal effects and the elasticities for households were averaged to obtain average marginal effects and elasticities for the quintile.

RESULTS

Results from the two specifications—the stratified sample approach and the spline regression approach—are shown in tables 7.7–7.9, which include the coefficients (from the Tobit regression) for population density and employment accessibility only. All the regression coefficients from a version of equation (1) fit on the full sample appear in appendix B.[14] The marginal effects and elasticities are presented in tables 7.10 and 7.11.

In table 7.7, the rows contain results from fitting equation (1) on the five population density subsamples. The table also shows the population density range for each quintile. Note that quintiles were split based on the full sample of 16,939 households. Given that some households had missing variables and

14. The results in appendix B are consistent with the literature. Note that the coefficient on distance from downtown Los Angeles in appendix B is negative, counter to simple expectations that people living distant from the central business district drive more. The regression also controls for access to employment through the gravity variable, which likely better controls for accessibility to Los Angeles's decentralized employment.

Table 7.7
Stratified Sample Approach: Neighborhood Population Density and Regional Employment Accessibility Coefficients, by Population Density Quintile

				Population Density, ¼-Mile Area		Gravity Variable for Employment Accessibility	
Population Density Quintile	**Minimum Density (persons/sq. mi. in surrounding ¼ mile)**	**Maximum Density (persons/sq. mi. in surrounding ¼ mile)**	**Number of Observations**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
1	0.00	2,578.34	2,139	–0.0004802	–0.18	**–0.1290879**	**–2.41**
2	2,583.44	5,034.40	2,330	0.0003823	0.12	**–0.1259769**	**–2.24**
3	5,039.49	7,485.35	2,435	0.0021975	0.77	*–0.1092746*	*–1.84*
4	7,490.45	12,122.29	2,522	0.0002719	0.21	–0.034606	–0.69
5	12,127.39	72,952.87	2,603	–0.0001099	–0.57	**–0.1140818**	**–2.62**
Full sample	0.00	72,952.87	12,029	0.0000316	0.18	**–0.1142238**	**–5.55**

Note: Coefficients that are statistically significant at the 5 percent level (two-tailed test) are bold; those significant at the 10 percent level are italic.
Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.

Table 7.8
Stratified Sample Approach: Neighborhood Population Density and Regional Employment Accessibility Coefficients, by Employment Accessibility (Gravity Variable) Quintile

				Population Density, ¼-Mile Area		Gravity Variable for Employment Accessibility	
Employment Gravity Variable Quintile	**Minimum of Employment Gravity Variable**	**Maximum of Employment Gravity Variable**	**Number of Observations**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
1	19.33	87.54	1,809	0.0020428	1.54	–0.2382835	–0.55
2	87.56	135.97	2,518	–0.0000936	–0.15	–0.0394491	–0.25
3	135.98	237.36	2,551	–0.0004998	–1.00	**–0.1694827**	**–2.25**
4	237.38	280.50	2,560	0.0000902	0.22	*–0.3620431*	*–1.94*
5	280.51	768.98	2,591	–0.0000835	–0.40	0.0039499	0.08
Full sample	19.33	768.98	12,029	0.0000316	0.18	**–0.1142238**	**–5.55**

Note: Coefficients that are statistically significant at the 5 percent level (two-tailed test) are bold; those significant at the 10 percent level are italic.
Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.

Table 7.9
Spline Regression Approach: Neighborhood Population Density and Regional Employment Accessibility (Employment Gravity Variable) Coefficients

		Coefficient	t-statistic
Population density quintile	1	–0.00040	–0.21
	2	0.00006	0.04
	3	0.00163	1.12
	4	–0.00061	–0.81
	5	–0.00001	–0.04
Employment accessibility quintile	1	–0.10523	–0.48
	2	**–0.19481**	**–2.43**
	3	**–0.08462**	**–2.01**
	4	**–0.25612**	**–2.96**
	5	–0.03545	–0.77

Note: Coefficients that are statistically significant at the 5 percent level (two-tailed test) are bold.
Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.

were excluded from the regression analysis, the number of households was not identical across the stratified samples used in the regressions. Table 7.8 shows results for the coefficients on the population density and employment accessibility variables when the sample is stratified by quintiles for the employment gravity variable.

Table 7.9 shows results from the spline regression approach, fitting equation (2) on the full sample. The general pattern of results in table 7.9 is similar to the pattern in tables 7.7 and 7.8. Population density is never significant, while employment accessibility is significant in the full-sample regression for equation (1). The elasticity of VMT with respect to employment accessibility implied by the full-sample estimate from table 7.7 is –0.29 (see table 7.10). That full-sample elasticity is similar to other estimates in the literature (Ewing and Cervero 2010; Tal, Handy, and Boarnet 2010). Tables 7.7 and 7.8 give little evidence of interactions between population density and employment accessibility, so we turn our attention to threshold effects of employment accessibility across different ranges of the employment gravity variable.[15]

15. Note, though, that the coefficients in tables 7.7 and 7.8 are not marginal effects, so while the coefficient on employment accessibility does not visually change much across different population density quintiles, the marginal effects could change across population density quintiles. Table 7.10, however, shows little variation in the marginal effect of employment accessibility across population density quintiles.

From the spline regression results for employment accessibility in table 7.9, the Tobit regression slope on the employment gravity variable varies across the different quintiles. Yet the pattern is not monotonic, as the magnitude of the coefficient becomes smaller when moving from the second to the third quintile and then grows larger in the fourth quintile. The coefficients in table 7.9 show impacts on the latent variable for the Tobit regression; for information on marginal effects and elasticities, we turn to tables 7.10 and 7.11.

Tables 7.10 and 7.11 show the average marginal effects and elasticities for households within quintiles for both the stratified sample and spline regression approaches. The quintile averages for population density, employment accessibility, and VMT are shown in table 7.12. Given that no coefficient on population density was statistically significant in any regression, we discuss only the marginal effects and elasticities for the employment accessibility gravity variable. Three sets of marginal effects and elasticities are shown in tables 7.10 and 7.11: basic regression, stratified regressions, and spline regression. The marginal effects and elasticities for the basic regression column use the full-sample regression coefficients from the bottom row of table 7.7 or 7.8, and evaluate the marginal effects and elasticities for each observation (or household) and average within the quintiles. The stratified regression and spline regression columns use the coefficients for each quintile from the respective approach.

Visual inspection reveals that the marginal effects in the basic regression column vary little across quintiles. The marginal effects in the stratified regressions column vary some, particularly in the fourth quintile, and the corresponding elasticities show substantial change. For example, in table 7.11 the elasticity of VMT with respect to employment accessibility is –0.29 for the full sample, –0.41 for households in the third quintile of employment accessibility, and –1.16 in the fourth quintile using comparisons to the stratified regression approach. In the spline regression column of table 7.11, the marginal effect of employment accessibility is –0.16 for households in the fourth quintile of employment accessibility, compared to –0.07 using equation (1) fit on the full sample, and the elasticity of VMT with respect to employment accessibility is –0.83 in the fourth quintile.

Overall, two conclusions are evident: employment accessibility is much more important than population density as a determinant of VMT in the SCAG data studied here; and (2) the impact of employment accessibility on VMT is largest for households in the third and fourth quintiles of employment accessibility. A comparison of marginal effects and elasticities in table 7.11 suggests that the larger part of the changes in elasticity across quintiles may be from changes in the household values for the employment accessibility and VMT variables, but the marginal effects in all but the "basic regression" also increase in the third and fourth quintiles. The elasticity in the fourth quintile, –0.83 (spline regression) and –1.16 (stratified sample), is approximately three to four times larger than common elasticities in the literature and our full-sample average elasticity from the basic regression. On net, we conclude that examining departures from regression

Table 7.10
Marginal Effects and Elasticities, by Neighborhood Population Density Quintile

	Effect of Population Density						Effect of Employment Accessibility					
	Basic Regression		Stratified Regressions		Spline Regression		Basic Regression		Stratified Regressions		Spline Regression	
Population Density Quintile	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity
1	0.00002	0.00043	–0.00034	–0.00671	–0.00028	–0.00545	**–0.08024**	**–0.14048**	**–0.09015**	**–0.16218**	–0.09387	–0.16782
2	0.00002	0.00142	0.00026	0.01570	0.00004	0.00271	**–0.07977**	**–0.20197**	**–0.08408**	**–0.20257**	**–0.09843**	**–0.24788**
3	0.00002	0.00232	0.00146	0.15125	0.00112	0.11895	**–0.07830**	**–0.25662**	*–0.07266*	*–0.23147*	**–0.10274**	**–0.32668**
4	0.00002	0.00376	0.00018	0.03352	–0.00039	–0.07195	**–0.07358**	**–0.33296**	–0.02296	–0.10473	**–0.09926**	**–0.41089**
5	0.00002	0.00893	–0.00007	–0.04144	–0.00001	–0.00278	**–0.06404**	**–0.46175**	**–0.07012**	**–0.61506**	–0.06403	–0.38447
Full sample	0.00002	0.00354	0.00031	0.03053	0.00010	0.00795	**–0.07485**	**–0.28578**	–0.06701	–0.26998	–0.09122	–0.31333

Note: Marginal effects and elasticities shown in bold are based on Tobit regression coefficients that are significant at the 5 percent level (two-tailed test); those shown in italic are based on coefficients significant at the 10 percent level. The full-sample marginal effects and elasticities in the stratified regression and spline regression columns are averages for all households across the five quintiles and so are based on five regression coefficients, some of which are significant for employment accessibility and some not. The full-sample marginal effects and elasticities in the basic regression columns are based on the coefficient estimate from using Tobit regression on equation (1) for the full household sample.
Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.

Table 7.11
Marginal Effects and Elasticities, by Regional Employment Accessibility (Employment Gravity Variable) Quintile

	Effect of Population Density						Effect of Employment Accessibility					
	Basic Regression		Stratified Regressions		Spline Regression		Basic Regression		Stratified Regressions		Spline Regression	
Employment Accessibility Quintile	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity	Mean Marginal Effect	Mean Elasticity
1	0.00002	0.00104	0.00128	0.05623	–0.00004	0.00864	**–0.07689**	**–0.09035**	–0.14888	–0.15909	–0.07096	–0.08302
2	0.00002	0.00195	–0.00006	–0.00563	0.00017	0.01834	**–0.07997**	**–0.14418**	–0.02720	–0.04850	**–0.13654**	**–0.24593**
3	0.00002	0.00245	–0.00036	–0.04363	0.00021	0.01712	**–0.07989**	**–0.24962**	**–0.12361**	**–0.41355**	**–0.05934**	**–0.18428**
4	0.00002	0.00431	0.00006	0.01218	0.00010	0.00135	**–0.07376**	**–0.36713**	*–0.23384*	*–1.15600*	**–0.16482**	**–0.82639**
5	0.00002	0.00715	–0.00005	–0.02291	0.00003	–0.00514	**–0.06457**	**–0.51504**	0.00236	0.02152	–0.02000	–0.15975
Full sample	0.00002	0.00354	0.00010	–0.00432	0.00010	0.00795	**–0.07485**	**–0.28578**	–0.10356	–0.36316	–0.09122	–0.31333

Note: Marginal effects and elasticities shown in bold are based on Tobit regression coefficients that are significant at the 5 percent level (two-tailed test); those shown in italic are based on coefficients significant at the 10 percent level. The full-sample marginal effects and elasticities in the stratified regression and spline regression columns are averages for all households across the five quintiles and so are based on five regression coefficients, some of which are significant for employment accessibility and some not. The full-sample marginal effects and elasticities for the basic regression columns are based on the coefficient estimate from using Tobit regression on equation (1) for the full household sample.
Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.

Table 7.12
Means, by Neighborhood Population Density Quintile and by Regional Employment Accessibility (Employment Gravity Variable) Quintile

	Descriptive Statistics				Descriptive Statistics		
Population Density Quintile	Mean Population Density	Mean Employment Gravity Variable	Mean Household VMT	Employment Accessibility Quintile	Mean Population Density	Mean Employment Gravity Variable	Mean Household VMT
1	1,177.74	108.59	58.53	1	2,717.01	66.56	54.93
2	3,898.63	153.30	57.52	2	5,208.96	109.82	57.72
3	6,230.60	188.90	53.90	3	6,555.44	189.20	55.77
4	9,518.46	231.17	47.62	4	10,556.06	258.31	46.94
5	19,897.63	286.98	32.69	5	15,745.24	323.66	34.16
Full sample	8,527.19	197.81	49.52	Full sample	8,527.19	197.81	49.52

Note: Mean values for the quintiles are for the subset of households for which all data are available and hence which were used to estimate the regression. Mean values for the full sample are for all 16,939 households.
Source: SCAG travel diary (NuStats 2003), census data, employment data; authors' calculations.

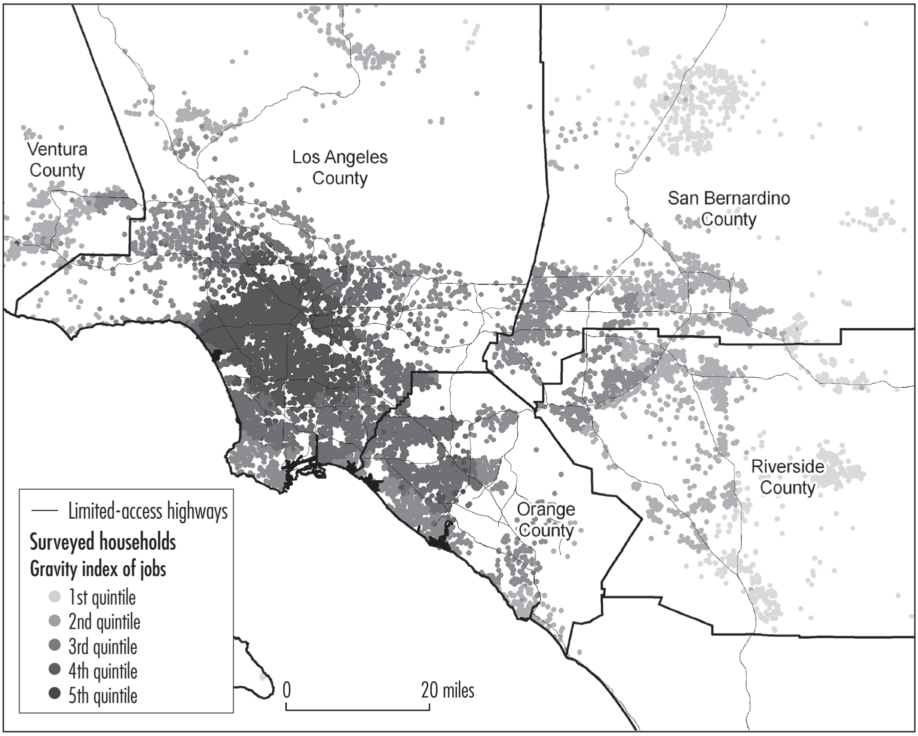
averages is important for land use–transportation research, and the third and fourth quintiles of employment accessibility appear to be fruitful places for policy attention.

Figure 7.2 shows employment accessibility quintiles by household location. The regression results suggest a focus on increasing employment accessibility or increasing the number of people living in those places corresponding to the third and fourth quintiles. This would direct policy attention primarily to north and central Orange County; the south-central part of Los Angeles; and some locations in the San Fernando Valley and near Ontario and Riverside, in what is called the Inland Empire (Riverside and San Bernardino Counties).

Figure 7.3 shows employment accessibility based on census tracts, not surveyed households. That view suggests a tighter policy focus, on the central spine of Orange County and areas extending from downtown Los Angeles. In general, we believe that a focus on employment accessibility would lead to prominent attention on the region's job subcenters.

Table 7.13 presents results for thresholds by distance from rail and bus stations. For distance from rail transit, we ran the full regression specification from equation (1), including dummy variables that indicate the concentric distance from a rail station: less than ⅛ mile, ⅛ to ¼ mile, ¼ to ½ mile, ½ to ¾ mile, and

Figure 7.2
Employment Accessibility Quintiles, by Household Location

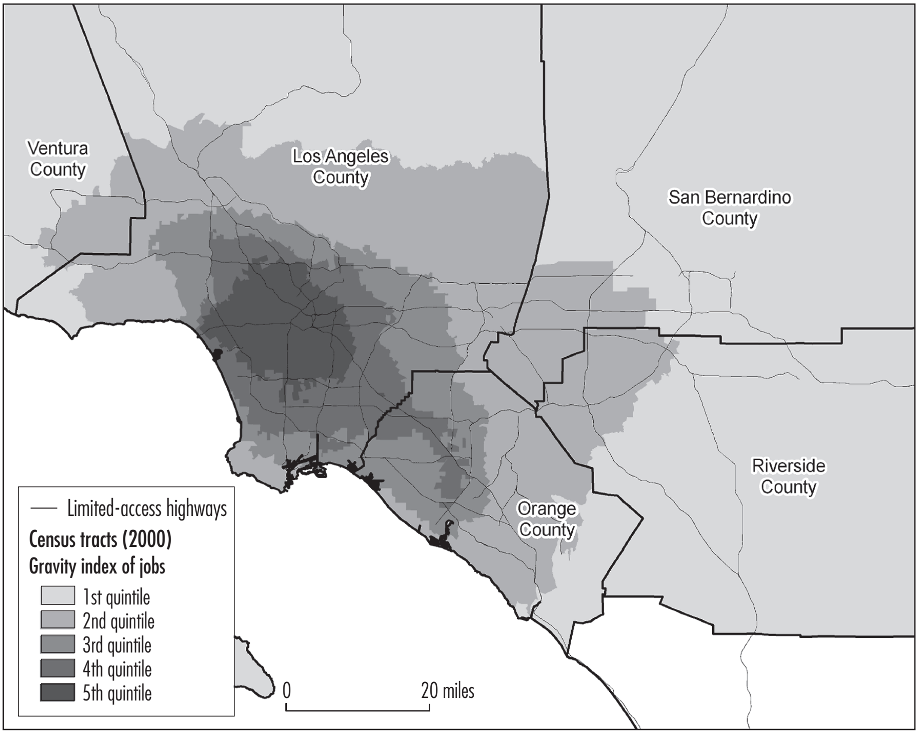


Source: Authors' calculations from SCAG 2001 travel diary (NuStats 2003) and employment data, year 2000, provided by SCAG.

¾ to 1 mile. We then ran the full regression specification with the same concentric circle dummy variables for distance from a bus station. In both regressions, the dummy variable indicating whether the household was inside a Compass 2% Strategy Opportunity Area was dropped, as the Compass areas overlap in transit access (by construction), and so colinearity might mask any effects of transit access. Table 7.13 presents the results for the concentric circle dummy variables only.

The results show no significant association between rail access and VMT. This might be due to the small number of households surveyed near existing rail stations. For example, there were 139 households within ¼ mile of a rail station, of which 25 were within ⅛ mile. Living near a bus station is associated

Figure 7.3
Employment Accessibility Quintiles, by Census Tracts



Source: Authors' calculations from SCAG 2001 travel diary (NuStats 2003) and employment data, year 2000, provided by SCAG.

Table 7.13
Rail and Bus Concentric Circle Dummy Variables

	Rail		Bus (Any)	
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**
<⅛ mile	–11.1903	–0.48	**–7.7698**	**–2.10**
⅛–¼ mile	–12.0599	–1.12	–4.0911	–1.12
¼–½ mile	–9.0098	–1.63	**–8.2585**	**–2.20**
½–¾ mile	–1.5748	–0.33	*–8.0430*	*–1.69*
¾–1 mile	2.7003	0.64	–0.9640	–0.16

Notes: From full regression without Compass dummy, regression was run once each for rail and bus dummy variables. Coefficients that are statistically significant at the 5 percent level (two-tailed test) are bold; those significant at the 10 percent level are italic.
Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.

Table 7.14
Distance from Freeway

	Coefficient	t-statistic	Number of Households
<10 miles from nearest freeway	**0.0011**	**3.06**	12,396
>10 miles from nearest freeway	0.0001	0.17	558
Full sample	**0.0004**	**2.80**	12,594

Note: From full regression. Coefficient is on distance from freeway, measured in meters, for households within10 miles from a freeway (top row) and farther than 10 miles from a freeway (second row). Coefficients that are statistically significant at the 5 percent level (two-tailed test) are bold.
Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.

with lower VMT. The ⅛-to-¼-mile ring was not significant, which is odd, but ignoring that, the pattern appears to be a relatively unchanged slope coefficient out to ¾ mile from the bus station, beyond which the relationship is statistically insignificant.

Table 7.14 presents results for thresholds by distance from a freeway. We found that distance from the nearest freeway was highly nonlinear. Both quadratic and cubic terms were significant in a regression with the full set of sociodemographic and land use variables. The nonlinearity appears to be driven by outliers, based on our initial analysis. When the sample is split into two groups, depending on whether the household is within 10 miles of the nearest freeway on-ramp, only the linear term for distance from the freeway is significant, and then only for households that are within 10 miles of an on-ramp. Table 7.14 suggests the intuitive finding that being closer to a freeway is associated with reduced VMT, but only for households that are within 10 miles.

Interpretation

Consistent with previous research, our results suggest that land use policies aimed at reducing VMT should focus on employment accessibility as opposed to neighborhood population density.[16] Our results also suggest that the link between employment accessibility and VMT varies in a nonlinear (threshold) fashion. The

16. For the 16,939 households in the SCAG travel survey, the correlation coefficient for population density and employment accessibility is 0.60. That illustrates how many land use variables are correlated, and population density has often been used in the literature to proxy a range of land use characteristics. Our results illustrate that, notwithstanding those correlations, VMT is only statistically significantly related to employment accessibility, echoing the finding of the larger literature that the magnitude of the VMT–employment accessibility relationship is larger than the magnitude of the VMT–neighborhood population density relationship.

association between VMT and employment accessibility is strongest in the mid-range locations—the third and fourth quintiles of employment accessibility.

One narrative that has developed in the land use–travel debate is that the magnitude of any association, even if it is causal, is too small to be important for policy purposes (Brownstone 2008; Brownstone and Golob 2009). If the results in this chapter are confirmed by further analysis, such a view would have to be tempered. The point is not that land use is a weak tool for influencing VMT, but that land use may be either a weak or a meaningful tool, depending on where policy is focused. Such a relationship is intuitive and was conjectured by the National Research Council's report *Driving and the Built Environment* (NRC 2009), but to the best of our knowledge, the evidence on thresholds presented in this chapter provides the first quantified illustration of such an effect. The results of this analysis carry a threefold message: (1) regional access is a more appropriate focus than neighborhood population density if the objective is VMT or GHG reduction; (2) some places will yield a stronger association with VMT than others; and (3) in the Los Angeles area, a focus on employment subcenters is likely a fruitful path for future research and policy.

What, then, of California's ambitious land use–transportation planning requirements set forth in SB 375? This legislation is still a work in progress. At the time this chapter was written, in the summer of 2010, the California Air Resources Board had just released draft transport-sector GHG emission targets for the state's 18 MPOs. By the fall of 2011, each MPO is required to develop sustainable community strategies (SCSs) that document how the MPO will comply with the transportation sector GHG targets for the years 2020 and 2035. Although there has been much speculation about the impact of SB 375, that speculation has occurred in advance of the MPOs' plans.

We suggest two possible paths for SB 375. One path would focus directly on employment accessibility, linking residences to job and activity centers through a combination of transportation infrastructure and land use planning. Such an approach would be consistent with the evidence presented in this chapter and, more important, is consistent with the legislative language of SB 375. Briefly, SB 375 requires each MPO to develop an SCS demonstrating that the MPO's regional transportation plan (RTP) and regional housing needs assessment (RHNA) are both consistent with GHG emission targets. The RTP is an MPO's program of infrastructure investment, possibly including travel demand management techniques. The RHNA is a plan to meet fair-share affordable housing requirements established by the state. In short, SB 375 is a requirement that transportation planning be coordinated with affordable housing strategies in ways that reduce GHG emissions—almost the policy translation of the analytical statement that employment accessibility, measured by a gravity variable, is key. Nothing in our analysis is at odds with SB 375, and we believe that future refinements of this analysis should be useful for SB 375 implementation.

Yet SB 375 might follow a different path, influenced more by ideas that focus on neighborhood-scale land use patterns rather than accessibility across the region. The popular imagery of land use–transportation links is informed by ideas from Smart Growth, transit-oriented development, and the New Urbanism. Those ideas are typically focused on neighborhood-scale design and land use, with an often explicit link to rail transit. Discussions of SB 375 often morph into a transit-oriented, Smart Growth view of the legislation. The evidence in this chapter suggests that a more mundane focus on employment accessibility will deliver larger VMT reductions. Certainly, neighborhood-level Smart Growth and transit-oriented development can be consistent with regional efforts to improve access to job centers. The difficulty lies not in any inherent tension between local and regional planning, but in the risk that a powerful neighborhood narrative will obscure the need to plan more regionally. SB 375, as written, offers an opportunity to focus on metropolitan-scale links between transportation access and land use. The results presented in this chapter suggest that maintaining a focus on the metropolitan scale, even while also fostering innovative local or neighborhood planning, will be vital.

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APPENDIX A: SOCIODEMOGRAPHIC AND LAND USE VARIABLES—DESCRIPTIVE STATISTICS

Sociodemographic Variable[a]	Mean	Std. Dev.	Min.	Max.
Number of persons in household	2.267	1.296	1	9
Number of bicycles in household	0.922	1.317	0	10
Homeowner = 1 if yes	0.608	0.488	0	1
English primary language at home = 1 if yes	0.917	0.276	0	1
Spanish primary language at home = 1 if yes	0.072	0.258	0	1
Household income level = 1 if in below category				
$10,000–25,000	0.157	0.364	0	1
$25,000–35,000	0.129	0.335	0	1
$35,000–50,000	0.148	0.355	0	1
$50,000–75,000	0.223	0.416	0	1
$75,000–100,000	0.130	0.336	0	1
$100,000–150,000	0.098	0.297	0	1
Over $150,000	0.054	0.226	0	1
Number of workers in household	1.158	0.842	0	6
Number of students in household	0.632	0.977	0	7
Number of licensed drivers minus vehicles	–0.152	0.759	–7	4
Number of persons under 16 in household	0.455	0.902	0	7
Number of persons with disabilities in household	0.104	0.337	0	3
Age of main respondent	46.543	16.720	0	95
Age of main respondent squared	2,445.753	1,692.631	0	9,025
Main respondent male = 1 if yes	0.471	0.499	0	1
Main respondent employed = 1 if yes	0.648	0.477	0	1
Main respondent's race/ethnicity = 1 if in below category				
White	0.656	0.475	0	1
Hispanic	0.197	0.398	0	1
African American	0.072	0.258	0	1
Asian/Pacific Islander	0.046	0.209	0	1
Main respondent's education level = 1 if in below category				
High school graduate	0.254	0.435	0	1
2 years of college/associate's degree	0.245	0.430	0	1
4 years of college/bachelor's degree	0.255	0.436	0	1
Postgraduate	0.154	0.361	0	1
Other	0.015	0.121	0	1

(continued)

Appendix A
(continued)

Sociodemographic Variable[a]	Mean	Std. Dev.	Min.	Max.
Travel diary included a Saturday = 1 if yes	0.090	0.286	0	1
Travel diary included a Sunday = 1 if yes	0.066	0.249	0	1
Household surveyed in fall 2001 = 1 if yes	0.333	0.471	0	1
Household surveyed in spring 2002 = 1 if yes	0.464	0.499	0	1

Land Use Variable[a]	Mean	Std. Dev.	Min.	Max.
Persons per sq. mi. within ¼ mile	8,527.193	7,699.033	0	72,953
Employment gravity variable (linear damping)	197.811	95.478	19	769
Commercial land use share within ¼ mile	8.713	11.926	0	98
Medium/high residential share within ¼ mile	12.892	17.294	0	98
Distance to nearest freeway on-ramp (meters)	3,055.287	6,101.653	1	86,014
Number of street intersections within ¼ mile	103.292	41.842	1	433
Fraction of those intersections that are four-way	0.246	0.179	0	1
Distance to Los Angeles City Hall (proxy for central business district)	55,046.910	45,176.290	276	357,987
Household within ¼ mile of rail station = 1 if yes	0.009	0.096	0	1
Household within ½ mile of rail station = 1 if yes	0.038	0.191	0	1
Household within ½ mile of bus stop = 1 if yes	0.868	0.339	0	1
Household within ½ mile of express bus stop = 1 if yes	0.272	0.445	0	1
Household within ½ mile of rapid bus stop = 1 if yes	0.143	0.350	0	1
Household in Compass 2% Strategy Opportunity Area = 1 if yes	0.311	0.463	0	1

[a] Statistics calculated for the 12,029 households used in the regressions.
Source: Sociodemographic variables are from the 2001 SCAG regional travel survey (NuStats 2003). Population counts are from the 2000 U.S. Census at the census block level. Employment counts are from employment data provided by SCAG for year 2000 at the census tract level. SCAG provided land use data for year 2000. The street network is from U.S. Census TIGER/Line files for year 2000. SCAG provided locations of rail stations and bus stops for 2006, and we removed rail stations opened after 2000.

APPENDIX B: REGRESSION RESULTS, EQUATION (1), TOBIT REGRESSION FIT ON FULL SAMPLE

	Coefficient	Std. Error	t-statistic
Persons per sq. mi. within ¼ mile	0.000032	0.000174	0.18
Employment gravity variable (linear damping)	−0.114224	0.020572	−5.55
Number of persons in household	14.345970	1.653724	8.67
Number of bicycles in household	0.054772	0.673829	0.08
Homeowner	5.430469	2.102542	2.58
English primary language at home	0.652045	7.921144	0.08
Spanish primary language at home	−9.739624	8.803417	−1.11
Household income level			
$10,000–25,000	17.722770	4.237788	4.18
$25,000–35,000	28.006450	4.387237	6.38
$35,000–50,000	34.952750	4.398933	7.95
$50,000–75,000	42.640510	4.362773	9.77
$75,000–100,000	42.289310	4.749126	8.90
$100,000–150,000	43.366690	5.003719	8.67
Over $150,000	47.719730	5.573739	8.56
Number of workers in household	7.222494	1.937953	3.73
Number of students in household	2.644149	1.265575	2.09
Number of licensed drivers minus vehicles	−4.148310	1.113866	−3.72
Number of persons under 16 in household	−13.864560	1.988888	−6.97
Number of persons with disabilities in household	−14.307080	2.641084	−5.42
Age of main respondent	1.069729	0.296083	3.61
Age of main respondent squared	−0.013879	0.002978	−4.66
Main respondent male (= 1 if yes)	5.329279	1.667394	3.20
Main respondent employed (= 1 if yes)	4.757199	2.822731	1.69
Main respondent's race/ethnicity			
White	10.968380	4.844847	2.26
Hispanic	4.783170	5.252993	0.91
African American	−1.111039	5.679793	−0.20
Asian/Pacific Islander	13.859130	6.108430	2.27

(continued)

Appendix B
(continued)

	Coefficient	Std. Error	t-statistic
Main respondent's education level			
High school graduate	19.424300	3.770977	5.15
2 years of college/associate's degree	26.261660	3.928971	6.68
4 years of college/bachelor's degree	28.757260	4.039997	7.12
Postgraduate	31.457440	4.297053	7.32
Other	33.863910	7.404212	4.57
Commercial land use share within ¼ mile	–0.107810	0.082520	–1.31
Medium/high residential share within ¼ mile	–0.065333	0.060908	–1.07
Distance to nearest freeway on-ramp (meters)	0.000470	0.000156	3.02
Number of street intersections within ¼ mile	–0.030230	0.021469	–1.41
Fraction of those intersections that are four-way	–17.428490	5.738423	–3.04
Distance to Los Angeles City Hall (proxy for CBD)	–0.000176	0.000039	–4.52
Household within ¼ mile of rail station	–3.094354	10.285560	–0.30
Household within ½ mile of rail station	–8.554579	5.377510	–1.59
Household within ½ mile of bus stop	0.134049	2.755370	0.05
Household within ½ mile of express bus stop	–2.131127	2.062802	–1.03
Household within ½ mile of rapid bus stop	0.610553	2.981448	0.20
Household in Compass 2% Strategy Opportunity Area	–4.087729	2.159362	–1.89
Travel diary included a Saturday	39.081790	2.876388	13.59
Travel diary included a Sunday	30.844950	3.295887	9.36
Household surveyed in fall 2001	1.123705	2.296653	0.49
Household surveyed in spring 2002	10.338650	2.235780	4.62
Constant	–58.073450	13.775350	–4.22
Sigma	84.8923	0.6164098	
Pseudo R^2 = 0.0178			
Number of households = 12,029	2,207 left-censored observations		

Source: Authors' regression analysis of SCAG travel diary (NuStats 2003), census data, employment data, and GIS data.