Final Report

Quantifying the effect of local government actions on VMT

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Principal Investigator: Deborah Salon

Contractor Organization: Institute of Transportation Studies, University of California, Davis

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ABSTRACT

To comply with AB 32 and SB 375, California local and regional governments are working to reduce vehicle miles traveled (VMT). To develop targeted policies with scarce resources, policymakers need guidance as to which policies will be most effective in their jurisdictions. This research uses empirical analysis of travel survey data to quantify how much Californians will change the amount that they drive in response to changes in land use and transport system variables. Our study improves upon past research in three key ways. First, we assemble and use a dataset that consists of merged information from five California-based household travel surveys that were conducted between 2000 and 2009. Second, we develop and employ a novel approach to control for residential self-selection, categorizing neighborhoods into types and using these as the alternatives in a predictive model of neighborhood type choice. Third, we focus on understanding heterogeneity in effects of variables on VMT across two important dimensions – neighborhood type and trip type. We find that the effects of some land use and transport system characteristics do depend on neighborhood type, in ways that are intuitive but had not previously been empirically verified. Results of this research are embedded in the VMT Impact spreadsheet tool, which allows users to easily see the implications of this work for any census tract, city, or region in California.

EXECUTIVE SUMMARY

Background

To comply with AB 32 and SB 375, California local and regional governments are working to develop and implement new policies that aim to reduce vehicle miles traveled (VMT). To develop targeted policies with scarce resources, cities, counties, and regions need guidance as to which policies will be most effective. The challenge is that the particulars of the local and regional context play a large role in determining which actions will be most effective where, but existing research provides little evidence on how context affects policy effectiveness. This project begins to fill this gap in the literature by estimating how the elasticities and marginal effects of policy-sensitive variables differ across trip purposes and local contexts.

Methods

The research goal of this project was to explore heterogeneity in how much Californians will change the amount that they drive in response to changes in land use and transport system characteristics. We explore heterogeneity across two important dimensions – neighborhood type and trip type – and use statistical analysis of travel survey and land use data to quantify these relationships. We control for key household and individual demographic characteristics and characteristics of the surveys themselves. We also control for household selection of residential neighborhood type.

This project used data from numerous sources and required the use of multiple statistical methods to estimate the effect of land use and transport system variables on VMT, differentiated by local context. To create the dataset, we merged observations from five household travel surveys conducted in California between 2000 and 2009, calculated the distance for each trip taken in a vehicle, and added variables to represent the built environment in the census tract where each household lived. These variables were derived from census data as well as calculated using GIS and MapQuest's Application Programming Interface (API).

Our final household estimation sample included complete observations for 52,975 weekday travel diaries from 45,624 households, some of which reported their travel on two days. This sample is much larger than any that we are aware of in the related existing literature. Our large sample is important because it allows us to obtain robust estimates of the effects we are interested in for each of seven distinct neighborhood types.

Our main analysis consisted of three steps. First, we used quantitative methods to classify census tracts into seven neighborhood types. Second, we estimated a multinomial logit model (MNL) of household choice of which neighborhood type to live in. Finally, we estimated tobit models of household weekday VMT, commute VMT for adult workers, and nonwork VMT for all adults for each neighborhood type. The tobit analyses are linked to the MNL model of neighborhood type choice as a means to control for residential self-selection. Tobit models are similar to linear regression analysis techniques, but more appropriately account for the significant percentage of zero VMT observations in our data. These models are the basis for calculation of the marginal effects and elasticities that are the main results of this project.

The land use and transport system characteristics for which marginal effects and elasticities were estimated in this research were gasoline price, local job access, regional job access, transit access, pedestrian and bicycle friendliness, percent of housing that is single family detached, road density (total road length per land area), and activity mix. All of the estimated relationships between these variables and VMT have the expected signs and were consistent in magnitude with those found in previous studies. A number of other variables were tested in these models, but they do not appear in our final analysis because their estimated effects were zero.

The final task in this project was to develop a spreadsheet tool that allows these research findings to be applied across the state in local government policymaking. The VMT Impact spreadsheet tool allows users to estimate the relationship between policy-sensitive variables and travel behavior for individual jurisdictions based on the neighborhood types that are present in that area.

Results

The contribution of this work is to estimate both average VMT and the effects of land use and transport system characteristics on VMT for different types of neighborhoods and for different types of trips. At the most basic level, we find that there are surprisingly large differences in average VMT across neighborhood types: the highest-VMT neighborhood type has three times the average VMT as the lowest.

We also find that the effects of some land use and transport system characteristics do depend on neighborhood type, in ways that are intuitive but had not previously been empirically verified. For instance, the effect of a change in gasoline price on VMT is effectively zero in both "Central City" and "Rural" neighborhoods. This likely reflects the fact that residents who drive in these neighborhoods do not have flexibility to choose to drive less when gas prices are high – they are already minimizing the amount that they drive. In all other neighborhood types, the VMT effect of pricing is uniformly large and statistically significant. The effect on VMT of improving job access is highly variable across neighborhood types, with the largest absolute effect of local jobs seen in the "Rural" and "Suburb, Single Family Homes" neighborhood types. As would be expected, changing road density is an important determinant of VMT only in neighborhoods with relatively lower road densities. Understanding the differences in effectiveness of policies on VMT will help to prioritize local actions to reduce VMT to comply with AB 32 and SB 375.

A rough scenario analysis indicates that marginal infrastructure changes within neighborhood types will yield reductions in VMT and greenhouse gas emissions on the order of 5 percent.

Conclusions

This research has shown clearly that there is considerable heterogeneity in both Californians' VMT and their estimated VMT response to changes in land use and transport system characteristics. These differences can be explained by categorizing neighborhoods. Looking forward, we suggest that studies of current policy "natural" experiments with before-after data collection be conducted, as these would provide a more direct link between on-the-ground actions and their VMT results.

INTRODUCTION

To comply with AB 32 and SB 375, California local and regional governments are working to develop and implement new policies that aim to reduce vehicle miles traveled (VMT). To develop targeted policies with scarce resources, cities, counties, and regions need guidance as to which policies will be most effective. The challenge is that the local and regional context play a large role in determining which actions will be most effective where, but existing research provides little evidence on how context affects policy effectiveness.

This project begins to fill this gap in the literature by estimating how VMT elasticities and marginal effects of policy-relevant variables differ across trip purposes and local contexts. Our goal is to use statistical analysis of travel survey and land use data to quantify the effect of certain local government actions (especially land use decisions) and other context-specific variables on vehicle miles traveled (VMT) in the state of California. We have created statistical models to predict both daily VMT by household and VMT for certain types of individual trips (i.e. commute, nonwork). Our models control for residential self-selection by explicitly modeling residential neighborhood type choice together with VMT.

Our innovation is a focus on the variation in behavioral response across trip purposes and local contexts. Local context is determined by the physical infrastructure that determines the travel options people have - including both transport infrastructure and built environment variables. For instance, people making a choice about how to get to work in San Francisco might realistically consider driving their car, riding the MUNI bus, riding BART, bicycling, or even walking (if they live close enough to their job). Such plentiful options are simply not available in other locations in California. In this research, we capture the effect of these differences in local transportation and built environment/land use context on behavioral response to policy.

Previous Literature

As part of this research, a portion of this research team summarized the impact of a broad number of policy variables on VMT through a survey of the literature. That summary has been published (Salon et al., 2012) and the full publication manuscript is attached as Appendix A of this report. Here we briefly highlight only the most pertinent parts of that broader literature review.

Most research on the determinants of VMT now uses individual or household travel diary data, and the typical approach (which we follow here) is to estimate a regression that explains VMT with a set of sociodemographic and land use characteristics. The key methodological issues that distinguish higher quality studies deal with data disaggregation and with residential selection.

Disaggregate data: Driving is a behavioral phenomenon, and it is difficult to understand behavior with data that are aggregated to units of geography (e.g. census tracts, cities, or even states). The modern literature on land use and travel, for the past two decades, has focused on disaggregate data on individuals and households as the units of analysis.

Residential self-selection: Residential self-selection refers to the possibility that people might choose where to live based in part on how they wish to travel (e.g. Cao, Mokhtarian, and

Handy, 2009.). If this is true, then it is a foregone conclusion that, for instance, people who live near transit will have higher rates of transit use (and relatively low VMT) and people who live in walkable neighborhoods will choose to walk for many of their trips (and relatively low VMT). Most studies of travel behavior use cross-sectional data, which usually does not include information relating to individual preferences about locations or transport modes.

Advanced econometrics, including instrumental variables and sample selection models, have been used to attempt to correct for this, and the work reported on here follows this model. These statistical methods do not allow for true causal inference as would a quasi-experimental research design with proper control group assignment and data collection before and after a built environment intervention occurs. Until many individual quasi-experiments are conducted and the data from them analyzed, however, cross-sectional data will continue to provide the basis for our understanding of the relationships between characteristics of the built environment and observed travel behavior.

The approach used here falls into the category of sample selection models, and represents a significant advance over previous studies that utilize similar methods. First, we use a quantitative method to classify census tracts into 7 distinct neighborhood types, rather than using the simpler urban/suburban split. Second, we analyze household selection of residential neighborhood into each of these neighborhood types. Finally, we use a VMT estimation method that both includes neighborhood type selection variables that were estimated in step 2 and accounts for the relatively large fraction of households and individuals that do not travel by vehicle on the assigned travel survey day.

Our findings indicate that, in fact, local context does affect VMT sensitivity to at least some types of changes in land use and transport system characteristics. This report details our data preparation, statistical analysis methodology, and results. As a companion product of this research, we have also developed the VMT Impact spreadsheet tool that is intended to be a user-friendly way to share our results with those making land use and transport system policy decisions in California.

DATA AND METHODS

The project for which this document is the final report utilized data from numerous sources and required the use of multiple statistical methods to arrive at estimates of the effect of land use and transport system variables on VMT, differentiated by local context. To create our dataset, we merged observations from five household travel surveys, calculated the distance for each trip taken in a vehicle, and added a number of variables to represent the built environment. Our analysis consisted of three main steps. First, we used quantitative methods to classify the census tracts of California into neighborhood types. Second, we estimated a multinomial logit model (MNL) of household choice between these neighborhood types. Finally, we estimated tobit models of VMT for each neighborhood type, connecting them to the MNL to control for residential neighborhood type self-selection. We estimated these models for three measurements of VMT: household total VMT, individual total nonwork VMT, and individual commute distance. Because our proposed analysis was complex, we first developed and tested our methods using only one of the travel surveys – the Caltrans Statewide Household Travel Survey – and later added observations from the remaining four surveys. This section of the report details each of these steps of data preparation and analysis.

Five Travel Surveys

In this project, we merge and analyze data that was collected in five separate travel surveys in California between the years of 2000 and 2009. The main reason for merging the data from multiple surveys was to increase the sample size for certain subsets of the data to improve statistical estimates of the relationships of interest. Although each travel survey on its own has a sufficient number of observations to estimate average effects of variables for the whole sample, we are interested in estimating these relationships separately for each of seven neighborhood types in the state, reducing the effective sample size for estimating each relationship dramatically. Furthermore, because we are focusing on variables that necessarily vary less within each neighborhood type than across the whole sample, identifying and estimating a statistically significant relationship requires a large number of observations in each neighborhood type. In the first stage of this project where we tested the methods using only the Caltrans Statewide survey, these issues caused many estimated relationships to be statistically insignificant. In the final analysis using five merged surveys, a large number of these relationship estimates became significant – both statistically and practically.

The surveys used include two statewide survey efforts (2001 Caltrans and 2009 NHTS) and three regional surveys (2000 Bay Area, 2000 Los Angeles area, and 2006 San Diego). We had originally planned to include data from a fourth regional survey conducted in 2000 in the Sacramento area. However, this survey did not record information about household ethnicity, which turns out to be an important determinant of neighborhood type choice. For this reason, we made the decision to exclude this data from our final analysis.

All of these travel surveys report information about the households surveyed, about each person in the household, and about each trip taken by a household member on one or two assigned travel diary days. Our research team has access to the latitude and longitude coordinates for every origin and destination for each trip taken on the travel diary days for all of these travel surveys. This information was used to calculate distances for each trip on the road network using the MapQuest API, providing us with the estimates of VMT that are used in this study. For some of these surveys, gaining access to the origin and destination location information required entering into confidentiality agreements with the stewards of the original data. As per these agreements, this research team has kept the data only on private computers or in password-protected locations on servers, and has not shared the information with others or used it for any purpose other than research.

The exact information collected by the different surveys differed somewhat. For instance, four out of the five surveys collected information about the educational attainment level of adult household members (the 2000 Bay Area survey did not), two out of five surveys collected information about the job types held by employed household members (2009 NHTS and 2000 Bay Area), and three out of five surveys collected information about the usual transport mode used by household members for their commute trips (2009 NHTS, 2006 San Diego, and 2000 Los

Angeles area). Because we are merging the data from the five surveys into one dataset for use in this analysis, we were only able to make use of variables that were common to all of the surveys. This is a limitation of our work, but we believe that the significant advantage that we get from creating this large merged dataset is worth the trade-off of the somewhat reduced set of variables that we can use in our empirical modeling efforts.

Table 1: Survey Sample Sizes, Total and Complete Observation Counts

Survey	Total Number of Household-Weekdays Recorded	Recorded Household-Weekdays With Complete Trip Data	Percent With Complete Trip and Household Data
BATS (2000)	26,161	19,502	75%
Caltrans (2001)	17,040	11,042	65%
NHTS (2009)	15,148	9,708	64%
SANDAG (2006)	3,651	2,592	71%
SCAG (2000)	13,879	10,131	73%

Table 1 indicates the total size of each survey's sample of weekday travel diaries together with the size of the sample that included all of the information needed for use in our analysis of the determinants of household VMT. All of the surveys had large numbers of weekday travel diaries that were missing at least one piece of key information for our study. The two pieces of information most likely to be missing were household income – which was missing for nearly 10 percent of households – and the spatial coordinates for at least one trip origin or destination for a car trip reported in the travel diary. Without fully geocoded trips for all household members, we could not calculate household VMT. This constraint forced us to drop a large number of households from our study.[1]

Dropping this many observations raises the question of whether the resulting sample that we use for analysis is representative of California's population. The answer is that it is not representative, but neither was the original full sample of households from these travel surveys. Below we describe the development of post-stratification weights for the estimation sample and report summary statistics for our dataset using these weights. Note that these weights are calculated based on only those households used in the estimations.

Land Use and Transport System Variables

To augment the travel survey data used for this analysis, we added a number of variables that characterized the neighborhoods that travel survey households lived in. All of these land use variables are specified at the geographic level of the census tract. These variables were derived from census data as well as calculated using GIS and other mapping software. The variables were used in our classification of census tracts into residential neighborhood types (described in

[1] Note that the values in Table 1 refer to the number of observations that was valid for our household VMT model. The number of household observations that can be used for each of our commute and nonwork VMT models is slightly higher because the constraint on spatial coordinate availability was less stringent. Specifically, spatial coordinates were needed for origins and destinations of commute trips and of all nonwork trips, respectively.

the next section of this report) and/or in our empirical analysis of the determinants of VMT. Some of these variables required substantial effort to create. We briefly describe each of them in turn here.

Direct Census Variables

A number of the variables in this category were taken directly from the 2000 Decennial Census and required minimal additional calculations. These include the tract population density, the percent of housing units that are vacant, the housing unit median value, the percent of housing units that are less than 10 years old, the percent of housing units that are more than 60 years old, the percent of housing units that are single-family detached, the percent of workers that commute by transit, and the percent of workers that commute by non-motorized means (i.e. bike or walk). All but the last of these were used in the census tract neighborhood type classification analysis, and the last three of them were used in the empirical model of VMT.

The choice to use census journey to work data to represent access to transit and the pedestrian and bicycle-friendliness of neighborhoods has pros and cons. An ideal measure of these variables would capture the access to desirable destinations offered by the bike/ped/transit infrastructure in a neighborhood in a consistent way throughout the state. For this project, we did not have the resources to develop a true accessibility measure for alternative modes, and therefore had the options to use census variables or to use measures of the physical transport system directly (e.g. number of transit stops or percentage of roads with sidewalks).

The two large advantages of the census data are that it is measured in a consistent way for all neighborhoods in the state, and that it captures not only that infrastructure is present in a neighborhood, but also something about the access that infrastructure provides for getting people where they need and want to go. If a large percentage of residents use these modes in a neighborhood, the modes must be providing access to desirable destinations. The disadvantage is that these data are also capturing something about the characteristics of the people who live in these neighborhoods that affects their propensity to use alternatives to the car (e.g. their incomes). A variable based on the presence of physical infrastructure would not confound resident characteristics with the availability of alternative modes, but it would also not capture the access offered by those modes to desirable destinations, which can be highly variable even for the same level of infrastructure. Because neither measure is clearly theoretically superior and the census data is measured consistently statewide, we opted to use the census variables in the present analysis.

Job Access Variables

Job accessibility of the home location has been shown in the literature to be an important determinant of VMT (see, e.g. Cervero and Duncan 2006). For this project, we used three job accessibility variables. We also tested a number of others that did not perform as well, and therefore do not appear in our final analysis. The three that we use are all calculated based on the 2003 Longitudinal Employer-Household Dynamics (LEHD) data available from the US

Census Bureau, which provides counts of jobs available in each census block.[2] The data is disaggregated further into industry type, but we did not make use of this feature for the current analysis. The data is based on unemployment insurance records kept at the state level and reported to the Census, and the location identifier is the address of the business where the employee works. As such there are inaccuracies in the number of jobs available by location when a large company with multiple offices does all of the unemployment insurance paperwork out of their main office (all company jobs get attributed to the main office census block). In addition, employers who do not pay into the state unemployment system for their employees are also not counted. That said, these data are the best available that have coverage of the whole state.

To generate job access variables using these data required the following steps. First, we calculated the distance from the centroid of every block group in the state to the centroid of every other block group. These distances were calculated "as the crow flies" rather than along the road network. Then, we dropped all distances that were more than 50 miles from our analysis. Using the remaining block groups within 50 miles, we calculated the simple inverse distance-weighted sum of the available jobs for each block group, divided into those jobs within 5 miles and those jobs between 5 and 50 miles from the block group centroid. Finally, we chose the block group with the highest population density in each census tract to represent the tract job access.

We experimented with three other jobs access variables in the process of this research: job density in the census tract, jobs within 5 miles of the census tract centroid, and a job accessibility measure calculated as described above except that the final value was a sum of jobs weighted by the inverse distance squared instead of simply by the inverse distance. We rejected each of these in favor of the measures we used. Tracts are too physically small in urban areas for the tract job density to be the best measure of even local job access. Total jobs within 5 miles is a useful measure, but weighting those jobs by distance is an improvement on this variable. Weighting by the inverse distance squared quickly renders jobs beyond 10 miles to have little effect on the variable, which we thought was too restrictive.

It is worth noting – as has been noted in the literature (Cervero & Duncan 2006) – that all jobs are not actually available to all workers and therefore a better measure of job accessibility would be one that represents a count of jobs in the relevant industry classification or at the relevant skill level for each worker. Unfortunately, as discussed in the previous section, much of the travel survey data that we use in this analysis does not include information about the type of job held by surveyed workers or the industry they work in, and the Bay Area Travel Survey does not include information about the educational attainment of survey respondents. It is for this reason that we use a total jobs access variable specification rather than a more targeted version of this variable.

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[2] Although most of the land use variables in this study are based on 2000 data, 2003 data is used for LEHD because this was the earliest year for which reliable LEHD data is available.

Activity Mix

In the existing literature, one land use variable that is often included in travel behavior studies is a measure of the mix of land uses in a neighborhood. Land use mix is usually based on the square footage of buildings in the neighborhood that is used for different purposes, and is commonly calculated using an entropy formulation:

$$Land\ Use\ Mix = \sum_{i=1}^{N} \frac{p_i * \ln(p_i)}{\ln(N)}$$

where p_i is the proportion of the total square footage in the neighborhood with land use i. This results in a land use mix variable that ranges from 0 to 1. Neighborhoods that have only one land use will have a land use mix value of 0, and neighborhoods that are evenly split between N possible land uses will yield a land use mix value of 1.

Because this study analyzes neighborhoods statewide, data limitations made it impossible for us to create a square footage-based representation of land use mix for all census tracts. As a closely-related substitute, this study uses an "activity mix" variable, calculated using the same basic entropy formula.

$$Activity\ Mix = \sum_{i=1}^{N} \frac{p_i * \ln(p_i)}{\ln(N)}$$

where p_i is the proportion of people (residents + employees) engaged in activity i in the neighborhood. In particular, our activity mix variable represents mixing of 5 categories in each census tract: residential population, and the number of jobs in each of four categories – industrial jobs, retail jobs, office jobs, and public sector jobs. The residential population data come from the 2000 Decennial Census, and the employment data come from the LEHD data described above. Although we do not have the data to perform a real comparison between land use mix and activity mix, we expect that these two variables should be highly correlated with one another.

Restaurant Access

In an attempt to account for access to destinations other than work locations, we used the MapQuest API to generate counts of restaurants from the MapQuest Points of Interest database within a 10 minute walk and within a 10 minute drive of each census tract centroid. We used these variables in our census tract neighborhood type classification analysis, but they are not included in our final specification for our empirical analysis of the determinants of VMT because they are highly correlated with the job accessibility variables and therefore do not add to the analysis.

Road Density

The road density variable used in this study is based on the GIS shapefile for the detailed street network in North America from the ESRI Corporation (maker of ArcGIS software products). It is a simple calculation of the total length of roadway per land area in each census tract in the state. We experimented with variations of this variable that were divided by type of roadway (e.g. highway, major arterial, small street), but did not find this detail to be useful for understanding the relationship between road infrastructure and VMT. We note that previous studies have specified lane-distances rather than our simpler specification of total road distance.

Gasoline Price

The data that we use for gasoline price is based on two main sources: zip code level data on regular gasoline prices in California in 2005 from the Oil Price Information Service (OPIS, a private data company), and the US Department of Energy's Energy Information Administration's (EIA) data on monthly average regular gasoline prices for California. We used the OPIS data to indicate the spatial distribution of gasoline prices (which we assigned to census tracts based on the zip code that the tract centroid was in), and the EIA data to indicate the change over time in gasoline prices in the state. Putting these together with the survey month and year for each household gave us an estimate of the gasoline price faced by that household on the travel diary day. We used the US Consumer Price Index to transform these prices into constant dollars so that the prices in different years would be comparable.

Classifying Census Tracts into Residential Neighborhood Types

One of the innovations in the research we have done for this project is our use of a quantitative method to classify census tracts into residential neighborhood types. The method employed here is similar to that used by Song and Knaap (2007). We use these neighborhood types in two important ways in our analysis. First, we use them as the choice set for a model of neighborhood type choice, which we join to our empirical model of VMT to control for residential self-selection. Second, we estimate separate effects of variables on VMT for each of these neighborhood types, which allows us to discuss the heterogeneity of the effect of policy-relevant variables on VMT across neighborhood types. Here, we provide a detailed account of our quantitative method of classifying census tracts into residential neighborhood types.

There are 5 steps to classify census tracts into neighborhood types using factor-cluster analysis:

1. Choose the raw data variables that will form the basis of the analysis.
2. Process these data using a principal factor analysis algorithm to create a new set of factor variables that retain the essential information from the raw data, but remove the collinearity between the original variables. Enough factors should be extracted to represent most of the variation in the original data.
3. Use these factors in k-means cluster analyses to identify different numbers of neighborhood types.
4. Compare the results for different numbers of clusters from step 3 to arrive at the number of neighborhood types that are represented in the data. There are a number of ways to compare cluster analysis results, but none of them are fully conclusive and some level of subjective judgment on the part of the analyst is required. The comparison methods used in this project included displaying the results graphically from cluster analyses in clustergrams, calculating the variation within clusters and the variation between clusters aiming to minimize the former and maximize the latter, and looking at the average values of standardized versions of the original variables for each cluster to check if there are multiple clusters that are virtually the

same. We also used our knowledge of a sample of real places within the data as a check on whether similar neighborhoods were clustered together.

5. Use GIS to create a map that displays the neighborhood type results for each census tract. This final step is important as a check on the usefulness of the entire analysis – we expect that if the factor-cluster analysis is working properly, census tracts of the same neighborhood type should cluster spatially.

The data used in this analysis was derived from the 2000 US Decennial Census, the 2003 Longitudinal Employer-Household Dynamics dataset from the US Census Bureau, a Detailed Street Network from ESRI, and the MapQuest point of interest search API. From those data, neighborhood types were derived based on a set of physical place-based variables, identified in Table 2.

Table 2: Variables used in California Neighborhood Type Classification

Variable	Data Source
Population Density in census tract	2000 Decennial Census
Job Accessibility (distance-weighted sum of jobs within 50 miles of census tract centroid)	2003 LEHD
Number of restaurants within 10 minute walk of the densest census block in each census tract	MapQuest API
Number of restaurants within 10 minute drive of the densest census block in each census tract	MapQuest API
Road density in the census tract	ESRI Detailed Street Network
Percent of workers in the census tract that commute by transit	2000 Decennial Census
Percent of housing units in the census tract that are vacant	2000 Decennial Census
Housing unit median value in the census tract	2000 Decennial Census
Percent of housing units in the census tract that are single-family detached	2000 Decennial Census
Percent of housing units in the census tract that are less than 10 years old	2000 Decennial Census
Percent of housing units in the census tract that are more than 60 years old	2000 Decennial Census

As a first step, each input variable was standardized to have a mean of zero and standard deviation of one for ease of cross-cluster comparison. Then, a factor analysis was conducted, reducing these 11 variables to 5 orthogonal factors. This step is important because raw variables that represent physical neighborhood characteristics are often highly correlated (e.g. housing unit density and road density), and cluster analysis algorithms weight each variable equally. This means that, for example, if a variable is put into a cluster analysis twice, then it will have twice the weight in the algorithm that creates the clusters. Factor analysis removes this collinearity between variables by creating a new set of 'factors' that can be thought of as distilling down the relationships represented in the original variables. In this particular case, 11 original variables that exhibited some level of correlation among them were replaced with 5 orthogonal factor variables. Each census tract was given a score on each of the five factors. A particular factor score was computed as a weighted linear combination of the 11 variables in Table 2, where the weights differ for each factor.

The next step in this process is to perform a k-means cluster analysis of the scores on the 5 orthogonal factors to identify to which cluster each census tract belonged. Cluster analysis is a powerful analytical tool, but requires an important decision to be made by the researcher: how many clusters to create. For this classification of California census tracts, we looked at cluster outputs for up to 10 clusters. We chose the number of main clusters to be 6 based on a combination of evaluation techniques, as described in step 4 above. When tracts were classified into 5 or fewer clusters, places that are distinct in key ways were grouped into the same cluster. When tracts were classified into more than 6 clusters, places that are similar in key ways were separated into different clusters.

The final step is to look at the resulting map of neighborhood types, and make sure that it looks reasonable. This final step is admittedly subjective, but is one that is seen as an important check on whether the method is working well. In this case, one of the clusters identified through the analysis – the "rural" neighborhood type – was more common in urban and suburban areas than we thought was reasonable. It turned out that the data were representing real aspects of these urban census tracts that made them group with the more rural areas – usually they had little development due to natural physical characteristics such as wetlands or steep grades. However, we decided to split the "rural" cluster into two neighborhood types based on whether or not the particular census tract was in a census-defined urbanized area.[3]

Our analysis resulted in 7 named neighborhood types in California, plus the category called "Preserved Land". The names for these neighborhood types were arrived at by looking at the mean values for standardized versions of the original 11 variables. Standardized variables have mean 0 and standard deviation of 1 over all census tracts in the state, so to the extent that the means for a particular cluster deviate from zero, that indicates ways that the cluster is distinct from the rest of the state.

Note: The values above are the mean values within each cluster of standardized versions of the variables listed. For the whole state, these variables have mean values of zero, so deviations from zero indicate differences between cluster averages and state averages.

Table 4 indicates their relative values using + and - signs, making them easy to interpret. For example, it is readily apparent that cluster 3 – which we designated as "Central City" – is much denser than the average census tract in the state, has better transit access, and has older housing stock. Cluster 4 – which we call "Rural" – is much less dense, cheaper, and has a higher vacancy rate than the average census tract in the state. Note that cluster 7 has virtually the same properties as cluster 4. This is because cluster 7 is the "Rural-In-Urban" cluster that we created separately from the data-based factor-cluster analysis. Table 5 describes each cluster in words and names them. In the remainder of this report, we will refer to clusters by their neighborhood type names rather than by their numbers.

Figure 1 through Figure 5 illustrate the spatial patterns of these neighborhood types for the entire state and for the four major metropolitan areas in the state: Sacramento, San Diego, San

[3] This decision was made in consultation with research division staff at ARB.

Francisco Bay Area, and Los Angeles. As is evident from these maps, the neighborhood types generated by the factor-cluster analysis method are largely spatially clustered as well, which is to be expected and provides some additional reassurance that the method is working to create reasonable delineations of neighborhood type.

Table 3: Average Values of Standardized Variables by Cluster

	1	2	3	4	5	6	7	8
N Tracts	1759	1777	82	626	1701	712	312	42
Restaurant Walk	0.02	-0.13	6.19	-0.3	-0.2	0.5	-0.1	MORE THAN 85% PRESERVED LAND
Restaurant Drive	0.77	-0.16	4.64	-1	-0.6	0.7	-0.8	
Road Density	0.6	0.29	1.38	-1.6	-0.6	1	-0.7	
Population Density	0.09	0.08	2.91	-0.8	-0.6	1.6	-0.6	
Jobs Access	0.87	-0.25	1.7	-1.1	-0.6	1.1	-1	
Percent Transit	-0.23	-0.11	3.6	-0.5	-0.4	2	-0.4	
Percent Vacant	-0.32	-0.13	0.2	1.2	-0.3	0	1	
Percent SFH	0.07	-0.42	-2	0.2	0.9	-1	-0.3	
House Value	0.25	-0.43	1.8	-0.5	0.5	-0.1	-0.6	
Percent New House	-0.43	-0.2	-0.4	0.4	0.6	-0.4	0.4	
Percent Old House	0	-0.3	3.2	-0.1	-0.4	1.4	-0.1	

Note: The values above are the mean values within each cluster of standardized versions of the variables listed. For the whole state, these variables have mean values of zero, so deviations from zero indicate differences between cluster averages and state averages.

Table 4: Cluster Average Values Transformed Into +/-

	1	2	3	4	5	6	7	8
N Tracts	1759	1777	82	626	1701	712	312	42
Restaurant Walk			++++	-		+		MORE THAN 85% PRESERVED LAND
Restaurant Drive	+		++++	--	-	+	-	
Road Density	+	+	++	--	-	++	-	
Population Density			++++	-	-	++	-	
Jobs Access	+		+++	--	-	++	--	
Percent Transit			+++	-	-	+++	-	
Percent Vacant	-			++	-		++	
Percent SFH		-	---		+	--	-	
House Value		-	++	-	+		-	
Percent New House	-		-	+	+	-	+	
Percent Old House		-	+++		-	++		

Table 5: Eight Neighborhood Types in Words

1	Urban Low Transit Use (N=1759)	Good accessibility, low vacancy, middle-aged housing stock (San Jose, Orange County, San Diego, LA outside downtown area)
2	Suburb With Multifamily Housing (N=1777)	Average on most indicators for the state, low single-family homes and low housing values
3	Central City Urban (N=82)	Very high density, excellent accessibility, high public transit access, low single-family homes, older high-value housing stock (mostly downtown SF)
4	Rural (N=626)	Very low access, high vacancy, high newer single-family homes with lower housing values (mainly outside population centers of any kind)
5	Suburb With Single-Family Homes (N=1701)	Low density and accessibility, low vacancy, high newer single-family homes and high housing values
6	Urban High Transit Use (N=712)	High density, good accessibility, high public transit access, low single-family homes, middle-aged and older housing stock (downtown LA, Berkeley, Oakland, San Francisco outside downtown area):
7	Rural-In-Urban (N=312)	These tracts have slightly better accessibility than the truly "rural" tracts, and are more likely to have multifamily housing (select tracts within urbanized areas that had been classified as "Rural")
8	Preserved Land (N=42)	Preserved Land

Note: "Accessibility" in the above table refers to a combination of job access and access to restaurants.

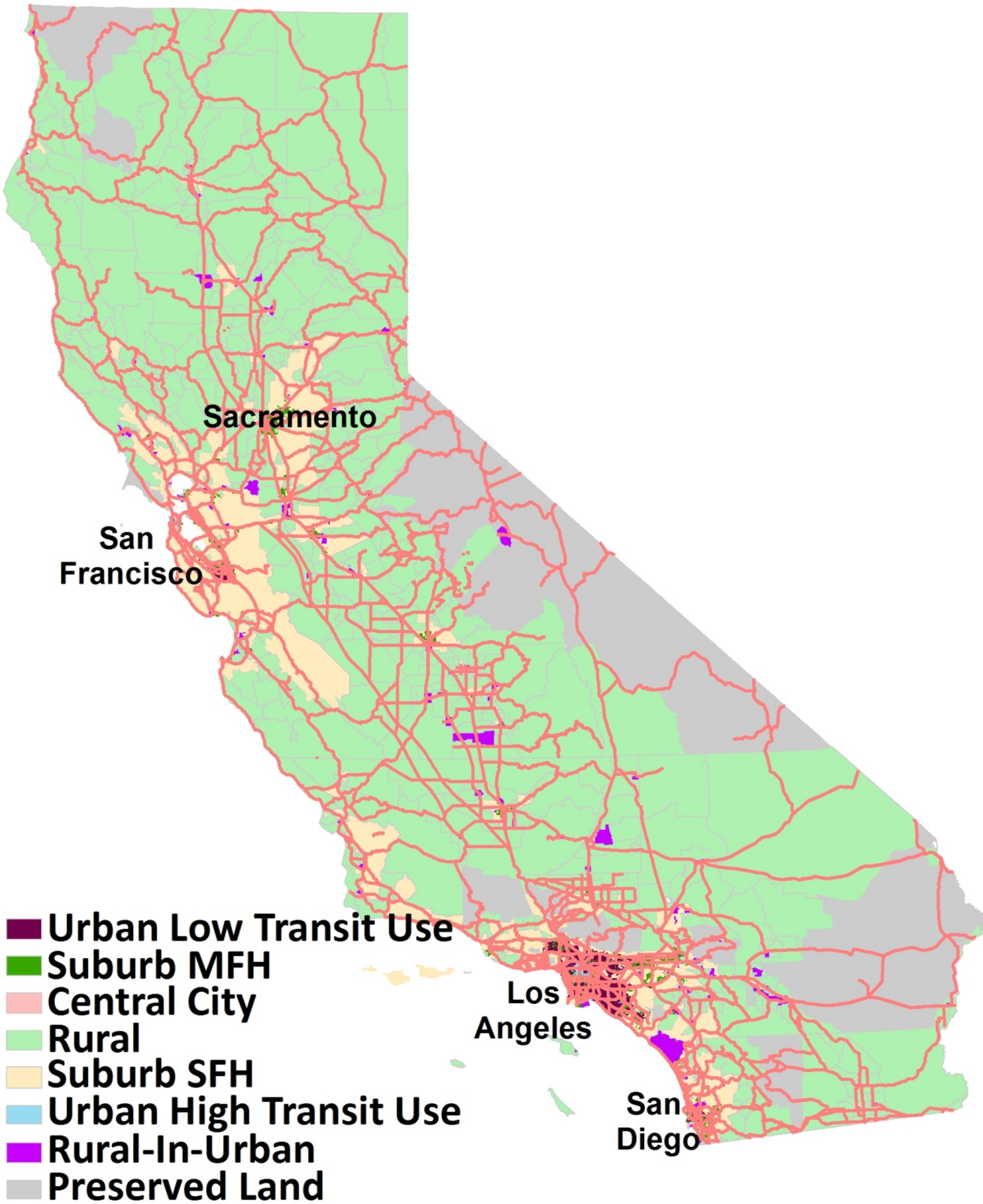

Figure 1: Map of Neighborhood Types for the State of California

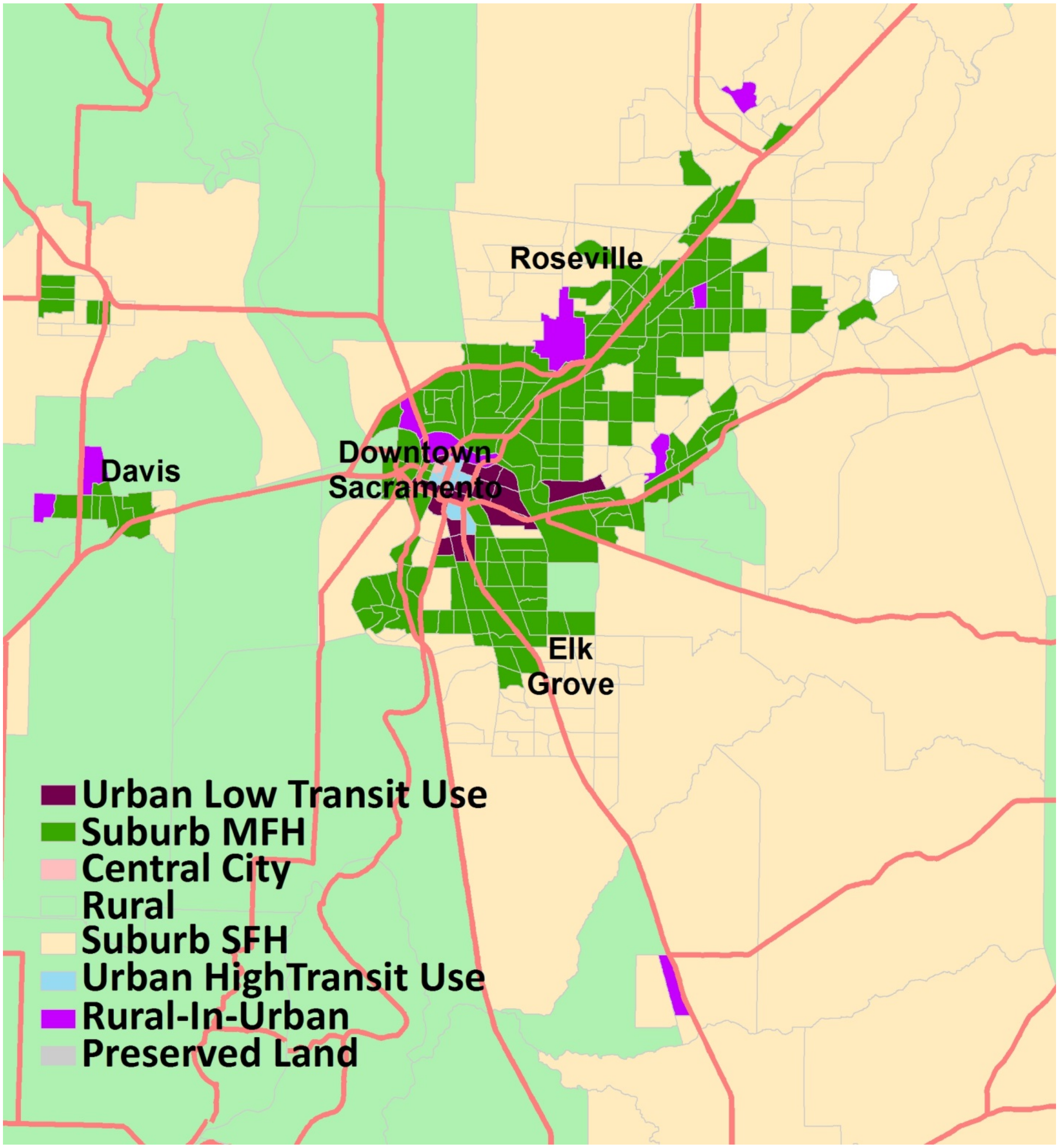

Figure 2: Map of Neighborhood Types in the Sacramento Area

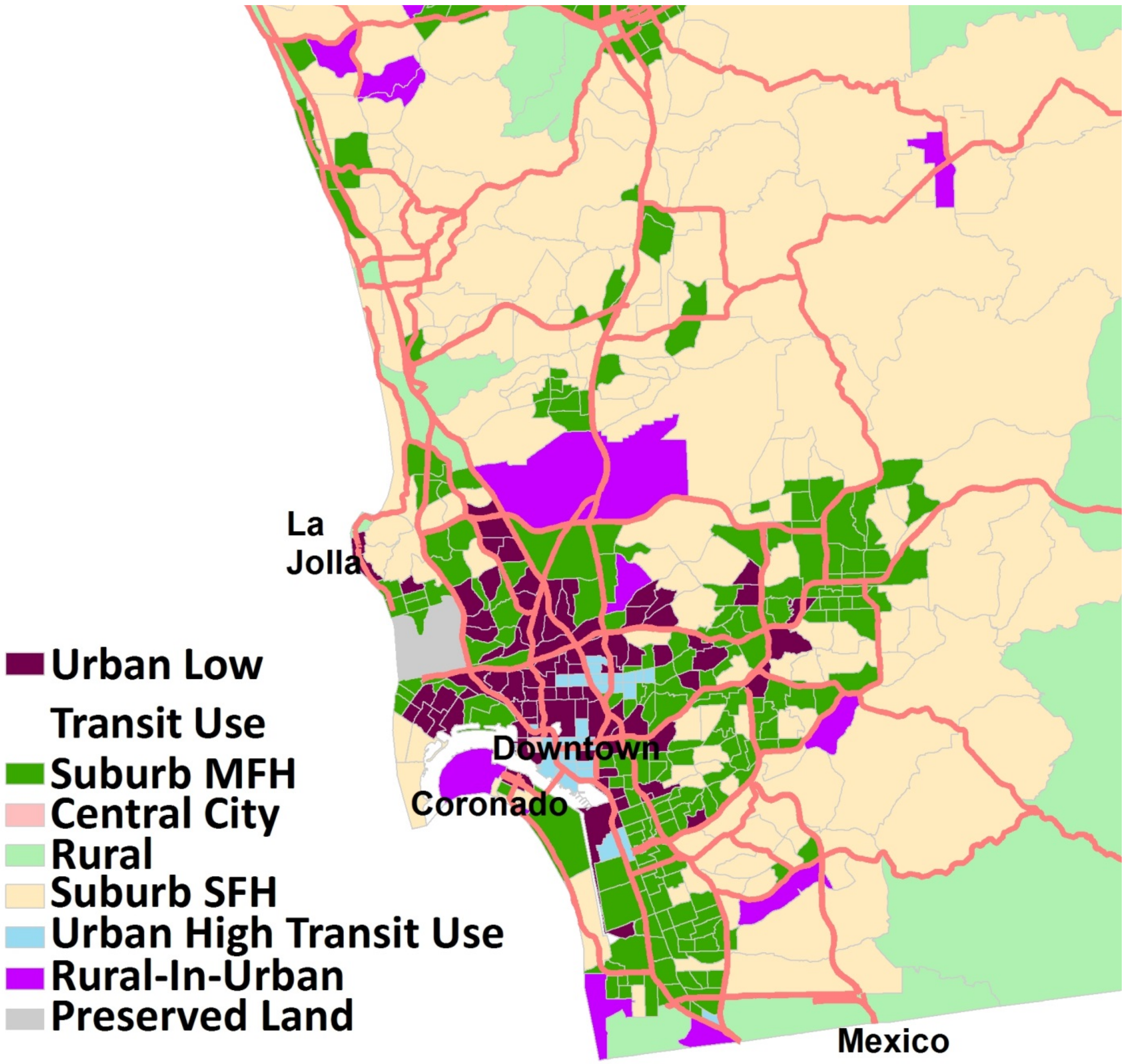

Figure 3: Map of Neighborhood Types in the San Diego Area

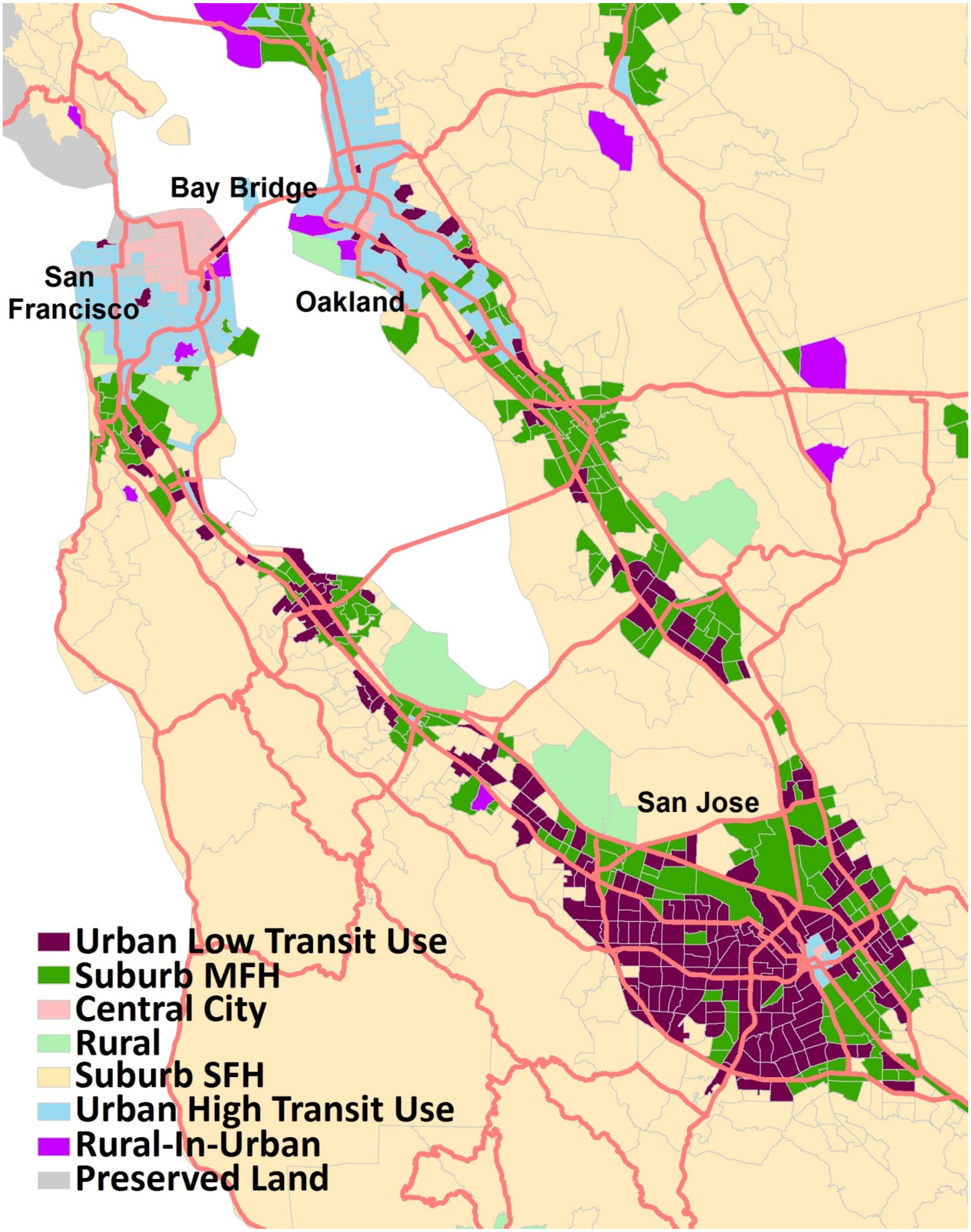

Figure 4: Map of Neighborhood Types in the San Francisco Bay Area

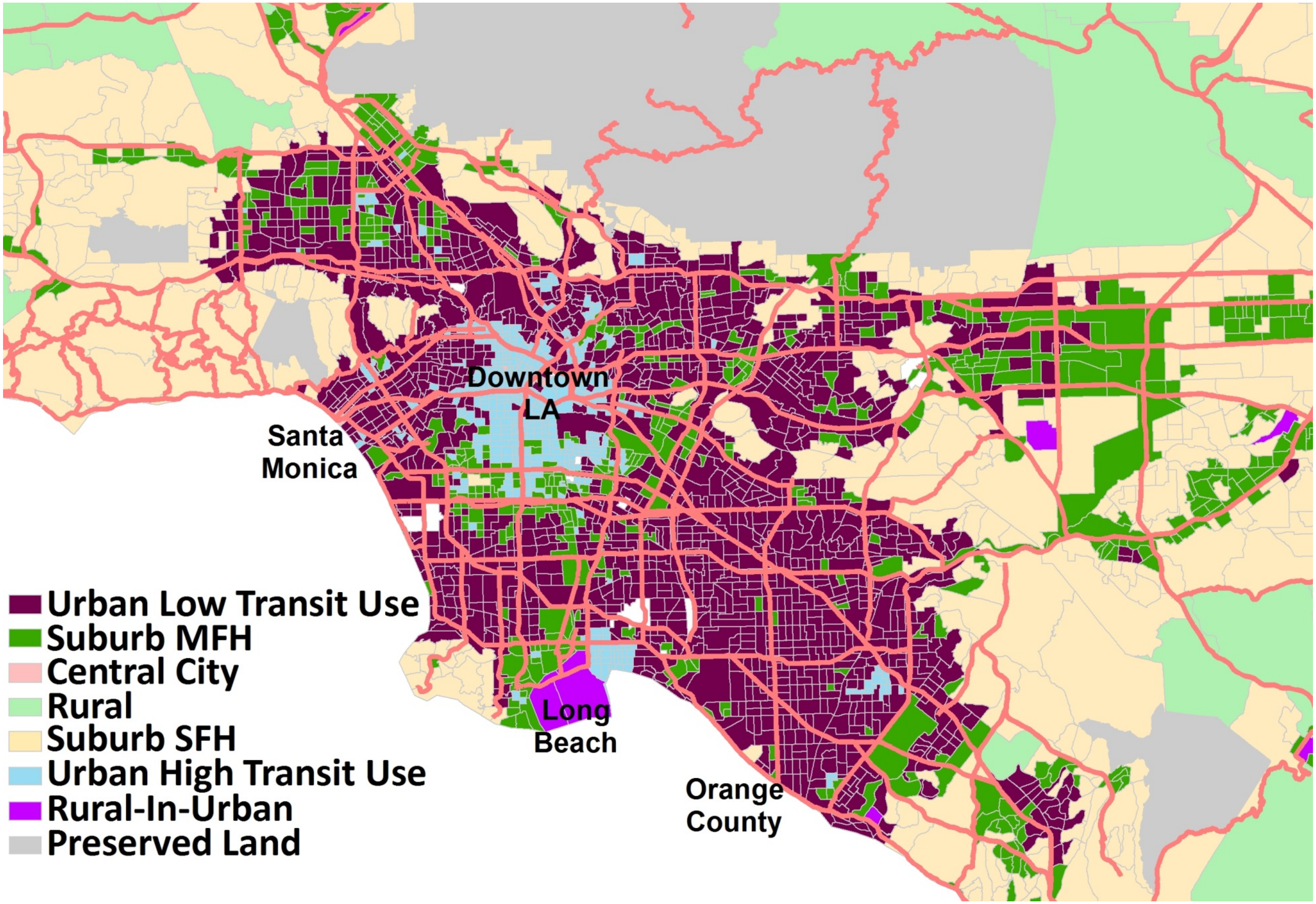

Figure 5: Map of Neighborhood Types in the Los Angeles Area

Generating Weights

In order to report summary statistics from our merged five-survey dataset that are representative of the population of California, we calculated and used post-stratification weights. Post-stratification weights are meant to adjust survey data to compensate for the fact that different types of people have different likelihoods of responding to the survey and being represented in the dataset.

Calculation of post-stratification weights is straightforward; they are simply the ratio of the percent of the population in each category to the percent of the sample in each category (see equation below). This insures that the weights have a mean of 1, and that therefore the sum of the weights equals the sample size. Each observation is weighted so that those categories that are over-represented in the sample compared to the population have weights that are less than 1, and those categories that are under-represented in the sample have weights that are greater than 1. Using these weights makes the weighted sample statistics more likely to reflect population statistics.

$$weight = \frac{percent\ of\ population\ in\ category\ i}{percent\ of\ sample\ in\ category\ i}$$

The challenge in calculating post-stratification weights comes in selecting the unit of analysis (in our case, household or individual) and the variables that define the categories. In this project, we developed weights for households, and used three variables for this purpose: income, residential neighborhood type, and life cycle stage. These variables are commonly used in creating travel survey data weights (see, for example, the NHTS weights development documentation), and are available in both the US Census data and in our full sample. Since most of our household travel survey observations were collected in or near the year 2000, we used the US 2000 Decennial Census as the basis for our population percentages in each category.

For the purpose of weighting our data, we divided household income into four categories: under $25,000, $25-$50,000, $50-$100,000, and over $100,000. To represent residential neighborhood type, we used the 7 types identified in our neighborhood classification analysis described in the previous section of this report (not including the "Preserved Land" category).

To represent life cycle stage, we divided households into 8 possible life cycle categories, listed and described in Table 6. As is clear from the table, we were unable to obtain a perfect match between the census definition and what we could put together from the travel survey data. In particular, there were two census definitions that we were unable to match. First, the census only lists related children in a household, while the travel survey includes all people living in a household regardless of relationship. We don't expect this to be a large difference since almost all children who are under 18 years of age live with relatives. Second, the census references all households to the age of the "householder" – defined as the person who is responsible for paying the housing costs – while the travel surveys reference all household members to the person who identifies as "self" when answering the survey. This may or may not be the same person in a given household. However, this difference is important only in differentiating between life stages 2 and 8, so we do not expect that it would have a large effect on our summary statistics tables.

Table 6: Comparison of Life Cycle Stage Definitions in US Census and in Travel Survey Data

Life Stage Code	Census Definition	Travel Survey Definition
1	one adult, 18-64, no children	one adult, 18-64, no children
2	2+ adults, householder 18-64, no children	2+ adults, at least one adult 18-64, no children
3	one adult, youngest related child 0-5	one adult, youngest child 0-5
4	2+ adults, youngest related child 0-5	2+ adults, youngest child 0-5
5	one adult, youngest related child 6-17	one adult, youngest child 6-17
6	2+ adults, youngest related child 6-17	2+ adults, youngest child 6-17
7	one adult, over 64, no children	one adult, over 64, no children
8	2+ adults, householder over 64, no children	2+ adults, all adults over 64, no children

Table 7 provides a comparison of the percent of census households in each category with the percent of travel survey households in each category. Poor households are under-represented in our sample, those living in the "Suburb, SFH" neighborhood type are over-represented, and (not surprisingly) households with small children are under-represented in our sample. From this table, it is clear that while our sample is certainly different from the state's population in a few of these categories, it is actually not too far off.

Because the census data is available as counts of households in each category, we used the method of iterative proportional fitting (IPF, a.k.a. raking) to create post-stratification weights for this dataset based on the three variables described above. To do this, we first calculated the percent of the state's households that had each combination of household income category and neighborhood type, and the percent of the state's households that is in each life stage. We then used the Stata package ipfweight to create the final weighting variable. The final household weights are calculated so that they have a mean of 1. The standard deviation of these calculated weights is 0.69, and the range is from 0.42 to 9.04.

Table 7: Comparison of Weighting Variables for US Census and Travel Survey Data

	Sample Percent	Census Percent
Household Income Category		
Under $25,000	17.4	25.5
$25,000 - $49,999	26.2	26.6
$50,000 - $99,999	35.3	30.7
$100,000 Or More	21.0	17.3
Census Tract Neighborhood Type		
Urban, Low Transit Use	18.3	25.2
Suburb, Multifamily Housing	23.4	26.5
Central City	1.9	1.5
Rural	10.4	8.5
Suburb, Single Family Housing	33.2	24.5
Urban, High Transit Use	8.2	9.1
Rural-In-Urban	4.6	4.4
Life Stage		
one adult, 18-64, no children	21.5	15.7
2+ adults, at least one adult 18-64, no children	35.8	25.8
one adult, youngest child 0-5	0.9	4.9
2+ adults, youngest child 0-5	9.5	14.4
one adult, youngest child 6-17	2.6	6.5
2+ adults, youngest child 6-17	12.1	14.1
one adult, over 64, no children	9.7	7.8
2+ adults, all adults over 64, no children	7.8	10.9

Using these weights insures that our state-level summary statistics reported below are representative of California's population in terms of these three important variables. All summary statistics reported here are weighted summary statistics.

Weights are not used in our statistical analysis of the determinants of VMT. The decision not to use weights in our multivariate model was made after consulting the statistical literature on the impact of the use of weights in both multinomial logit and regression models. In the case of using weights in multinomial logit models, the literature clearly directs that this is not necessary (Ben-Akiva & Lerman 1985). In the case of ordinary least squares regression, the jury appears to still be out on the advantages and disadvantages of using weights in estimation (for a full recent discussion of this issue, see Gelman 2007 and comments associated with this paper in *Statistical Science*, 22(2)). To the extent that relevant weighting variables are controlled for using explanatory variables in the estimation itself, weights should not be necessary. Even when these variables are not available for use in the regression equation, it is not clear that using weights in the analysis improves the results. In our models, we do include the variables we use for weighting in our estimation – income and life stage as explanatory variables, and neighborhood type to stratify the sample for analysis.

Summary Statistics for Full Dataset

To provide a bit more context for our analysis of the determinants of VMT, this section describes some key summary statistics for the full merged dataset that we have assembled. All of these summary statistics are calculated using the post-estimation weights described above.

Perhaps most importantly, we begin with a histogram that illustrates the distribution of our main dependent variable: Household Weekday VMT (see Figure 6). To make it easier to read, this histogram does not include the nearly 15% of households in our sample that reported zero VMT, and the 2% of households reporting a weekday VMT greater than 200 miles are also not shown. The pattern is clear, with more households having relatively low VMT on the travel survey diary day. As is reported in the tables that follow, the mean weekday household VMT for our sample is 44.9 miles, and the standard deviation of the distribution is 55.1 miles.

Table 8 looks specifically at those households that have zero VMT on their travel diary survey day and compares them with households that have nonzero VMT using four indicator variables. There are two types of zero VMT households – those that did not make trips, and those that made trips, but did not use vehicles for those trips. It turns out that these two categories of zero VMT households have different demographic profiles from each other, and also from those households that did travel by car. Both of the zero VMT household types are much more likely to also be zero vehicle households and much more likely to be poor than nonzero VMT households. Those in the "alternative mode only" category are by far the most likely to be vehicle-free, and also the most likely to be poor. For the other two indicator variables listed in Table 8, one type of zero VMT household is similar to nonzero VMT households. Zero trip households are more likely than either "alternative mode only" or nonzero VMT households to be senior citizens. "Alternative mode only" households are more likely than either zero trip or nonzero VMT households to live in neighborhoods that are highly transit accessible.

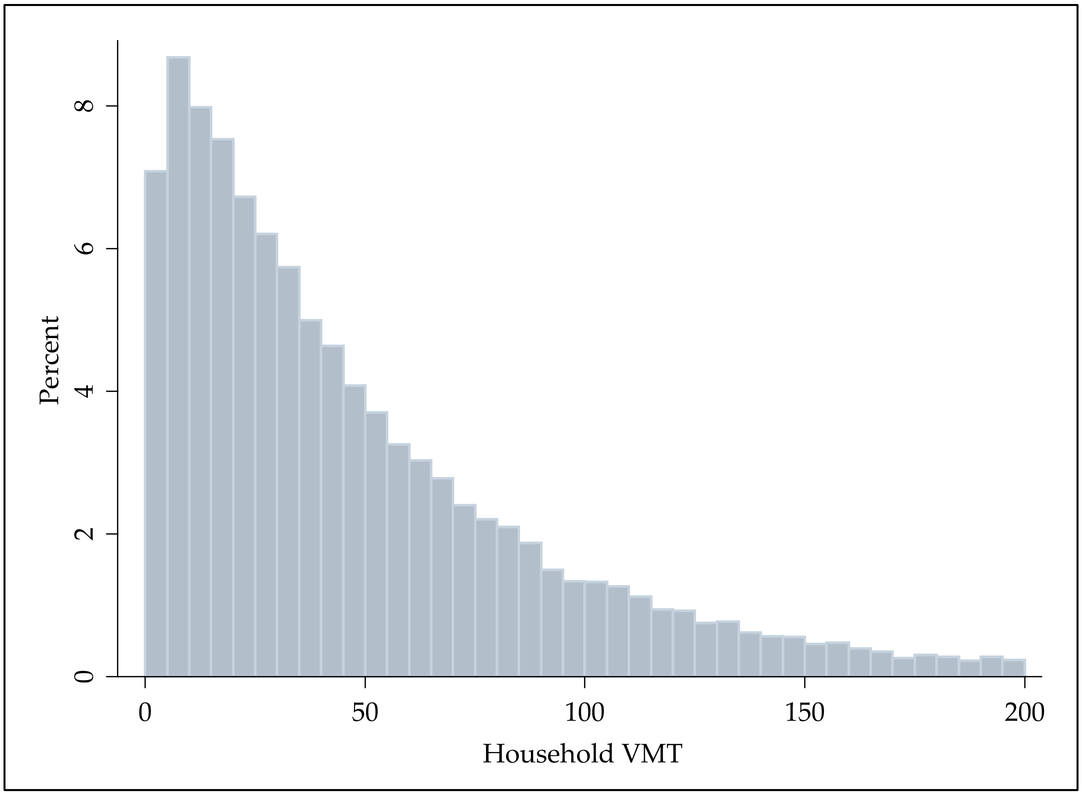

Figure 6: Household Weekday VMT Distribution for Nonzero VMT ≤ 200 Miles

Table 8: Summary Statistics Comparison between Zero and Nonzero VMT Households

	Zero Trips	Alt Mode	Nonzero VMT
Percent of HH that are car-free	17.1%	57.1%	2.1%
Percent of HH in low income bracket (<$25K)	49.2%	61.7%	20.0%
Percent of HH over 64 with no children in HH	41.6%	18.1%	16.4%
Percent of HH in Central or Urban High Transit Use Neighborhoods	9.6%	37.6%	8.6%
N	4598	3024	45353

Table 9 through Table 14 provide basic distributional statistics for six key variables along with the mean and standard deviation of household VMT within each category of these variables. The key variables are life stage, region of the state, day of the week that the survey was conducted, income category, neighborhood type, and household size. Note that for the three variables used in creating the weights, their weighted basic distributional statistics match the census.

Mean household VMT varies substantially across the categories of these variables, largely as expected. Households with younger adult members travel more than households composed of older adults (Table 9). Children appear to be associated with higher mean VMT (Table 9).

Overall, the more members in a household, the higher the household VMT will be (Table 10). Higher income is also strongly associated with higher household VMT (Table 11).

Compared to these demographic variables, survey day of the week and region of the state are associated more weakly with household VMT. Weekday household VMT is lowest in the most rural regions (Northern CA and Mountains) and highest in the San Francisco Bay Area (Table 12). Interestingly, household VMT is significantly lower on Mondays than on other weekdays (Table 13).

Finally, and most importantly for this research, there is a large difference in mean weekday VMT between neighborhood types in this dataset (Table 14). The neighborhood type of "Central City" has a mean household weekday VMT of under 18 miles, while those households living in the "Suburb, SFH" neighborhood type have a mean household weekday VMT of nearly 60 miles. While this difference certainly has something to do with the demographic characteristics of the households that choose to live in each neighborhood type, the three-fold difference in VMT is striking. Figure 7 illustrates this data in a bar chart, ordering the neighborhood type categories from lowest to highest mean weekday household VMT.

Because these differences in VMT between neighborhood types are one of the key findings of this research, included here are tables and figures illustrating these data for both individual adult Nonwork VMT and for individual Home-to-Work Commute VMT (see Table 15 through Table 17, and Figure 8 and Figure 9). Although the exact order of the neighborhood types differs slightly between these different types of VMT, the main message is clear: average VMT varies dramatically by neighborhood type.

Table 9: Life Stage Distribution of Travel Survey Data and Household VMT by Life Stage

Life Stage	N	Percent	Mean HH VMT	SD HH VMT
one adult, 18-64, no children	8293	15.7	24.79	33.47
2+ adults, at least one adult 18-64, no children	13682	25.8	50.56	52.70
one adult, youngest child 0-5	2579	4.9	33.31	43.54
2+ adults, youngest child 0-5	7604	14.4	66.38	68.25
one adult, youngest child 6-17	3456	6.5	35.89	44.72
2+ adults, youngest child 6-17	7444	14.1	71.71	68.21
one adult, over 64, no children	4153	7.8	14.26	26.52
2+ adults, all adults over 64, no children	5765	10.9	30.11	42.42
Total	52975	100.0	44.90	55.10

Table 10: Household Size Distribution of Travel Survey Data and Household VMT by Household Size

Household Size	N	Percent	Mean HH VMT	SD HH VMT
1	12423	23.5	21.02	31.23
2	20075	37.9	40.01	46.57
3	8571	16.2	55.57	56.86
4	7555	14.3	68.34	67.03
5	2922	5.5	72.87	73.68
6 or more	1429	2.7	76.20	89.02
Total	52975	100.0	44.90	55.10

Table 11: Income Distribution of Travel Survey Data and Household VMT by Income Category

Income Category	N	Percent	Mean HH VMT	SD HH VMT
Less than $25,000	13501	25.5	22.69	39.97
$25,000 - $50,000	14084	26.6	38.20	49.64
$50,000 -$75,000	16244	30.7	56.23	59.28
More than $100,000	9146	17.3	67.88	60.32
Total	52975	100.0	44.90	55.10

Table 12: Regional Distribution of Travel Survey Data and Household VMT by Region

Region	N	Percent	Mean HH VMT	SD HH VMT
Northern California	1824	3.4	38.50	49.95
Sacramento Area (SACOG)	1270	2.4	40.59	44.14
San Francisco Bay Area (ABAG)	20576	38.8	49.73	55.15
Central Coast	1253	2.4	43.40	60.62
San Joaquin Valley	3287	6.2	39.71	54.59
Mountains	400	0.8	38.00	58.04
Los Angeles Area (SCAG)	17991	34.0	44.07	59.61
San Diego Area (SANDAG)	6374	12.0	37.77	40.69
Total	52975	100.0	44.90	55.10

Table 13: Day of Week Distribution of Travel Survey Data and Household VMT

Day of Week	N	Percent	Mean HH VMT	SD HH VMT
Monday	11800	22.3	42.98	55.14
Tuesday	10897	20.6	45.87	53.62
Wednesday	10216	19.3	45.27	53.44
Thursday	9294	17.5	44.94	53.90
Friday	10768	20.3	45.63	58.94
Total	52975	100.0	44.90	55.10

Table 14: Household VMT by Neighborhood Type

Neighborhood Type	N	Percent	Mean HH VMT	SD HH VMT
Urban, Low Transit Use	13391	25.3	41.70	47.38
Suburb, Multifamily Housing	14083	26.6	40.99	53.40
Central City	821	1.5	17.45	33.07
Rural	4529	8.5	50.27	63.60
Suburb, Single Family Housing	13017	24.6	59.66	61.99
Urban, High Transit Use	4814	9.1	26.80	39.97
Rural-In-Urban	2320	4.4	41.09	59.33
Total	52975	100.0	44.90	55.10

Table 15: Individual Nonwork VMT by Neighborhood Type: All Adults

Neighborhood Type	N	Percent	Mean Nonwork VMT	SD HH VMT
Urban, Low Transit Use	19486	25.3	11.40	22.44
Suburb, Multifamily Housing	22555	26.6	11.00	23.70
Central City	1660	1.5	5.22	15.45
Rural	11758	8.5	16.66	31.11
Suburb, Single Family Housing	38980	24.6	14.28	25.12
Urban, High Transit Use	8241	9.1	7.44	18.56
Rural-In-Urban	4854	4.4	13.23	28.40
Total	107534	100.0	12.07	24.31

Table 16: Individual Nonwork VMT by Neighborhood Type: Adults Making at Least One Nonwork Trip

Neighborhood Type	N	Percent	Mean Nonwork VMT	SD HH VMT
Urban, Low Transit Use	16,810	25.3	17.63	25.87
Suburb, Multifamily Housing	17,678	26.6	17.60	27.90
Central City	1,031	1.5	7.19	17.93
Rural	5,685	8.5	28.85	36.50
Suburb, Single Family Housing	16,340	24.6	21.70	28.28
Urban, High Transit Use	6,043	9.1	10.96	21.29
Rural-In-Urban	2,912	4.4	21.64	33.51
Total	66,499	100.0	18.99	28.31

Table 17: Individual Home-to-Work Commute VMT by Neighborhood Type

Neighborhood Type	N	Percent	Mean Home-to-Work VMT	SD HH VMT
Urban, Low Transit Use	11,292	25.3	9.43	9.80
Suburb, Multifamily Housing	11,972	26.6	10.05	11.59
Central City	699	1.5	5.48	10.12
Rural	3,865	8.5	12.35	15.62
Suburb, Single Family Housing	11,088	24.6	13.22	17.45
Urban, High Transit Use	4,075	9.1	7.82	10.36
Rural-In-Urban	1,980	4.4	9.90	14.12
Total	44,970	100.0	10.59	13.42

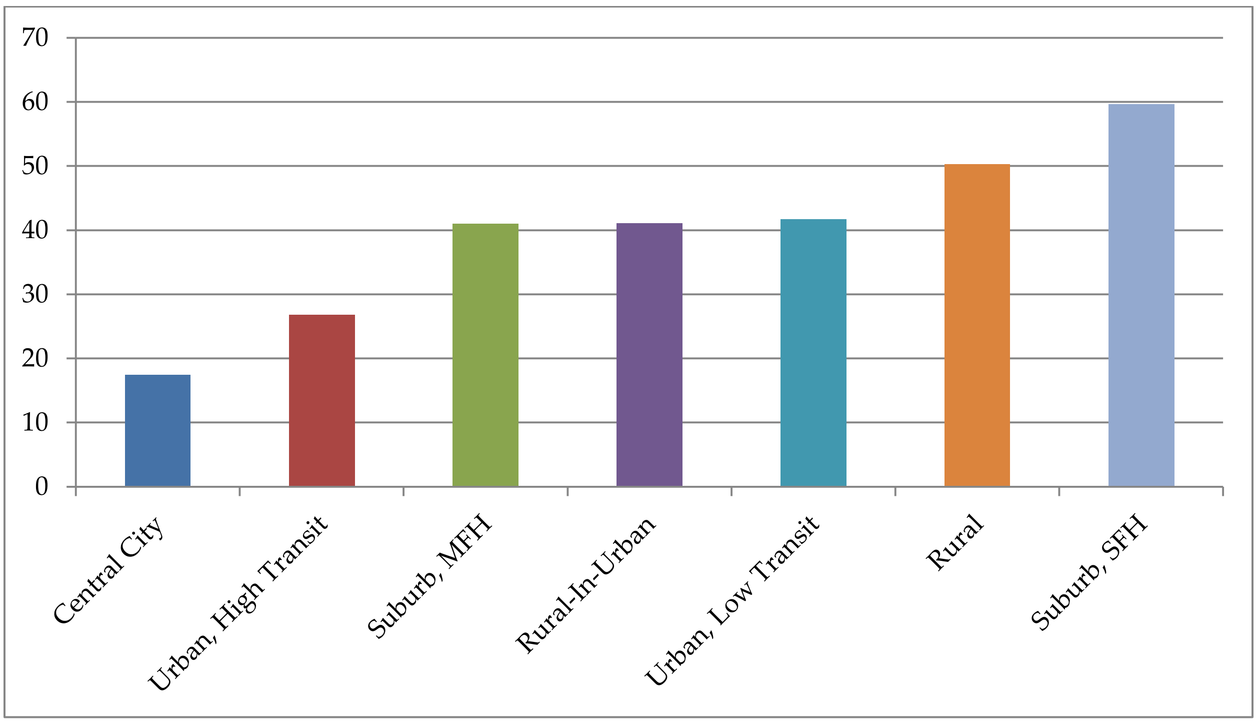

Figure 7: Average Household Weekday VMT by Neighborhood Type

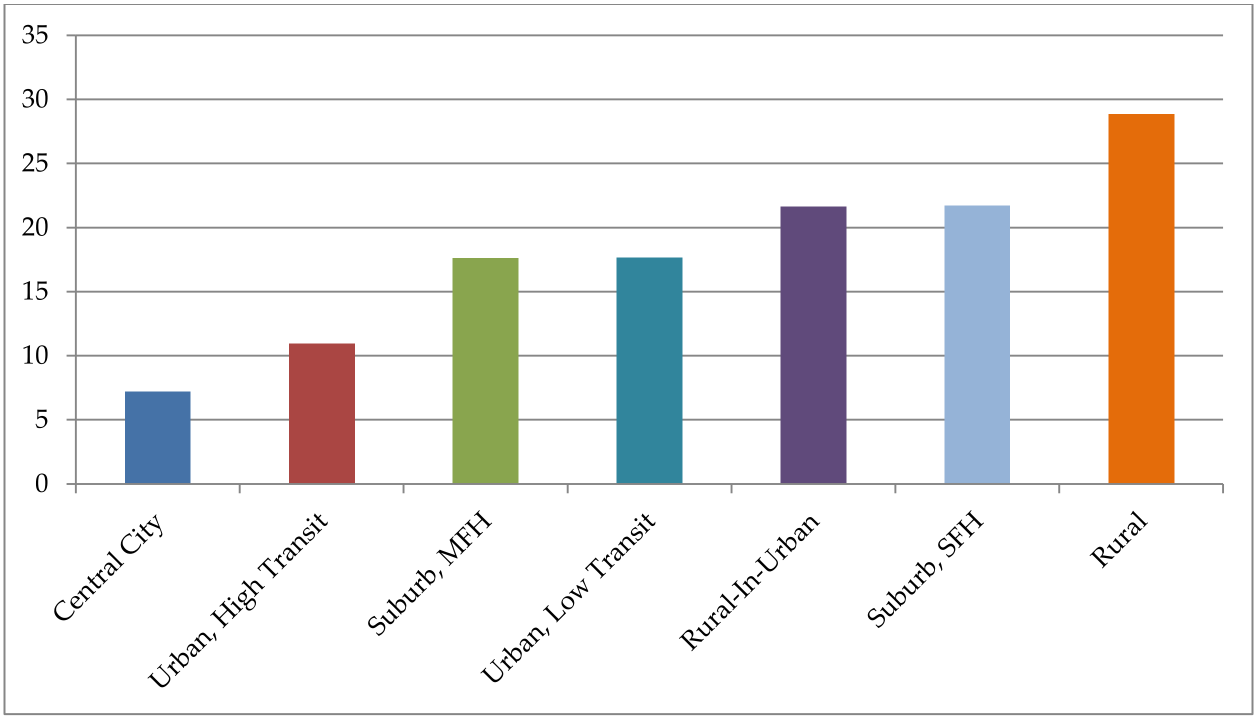

Figure 8: Average Weekday Nonwork VMT by Neighborhood Type Among Adults Making at Least One Nonwork Trip

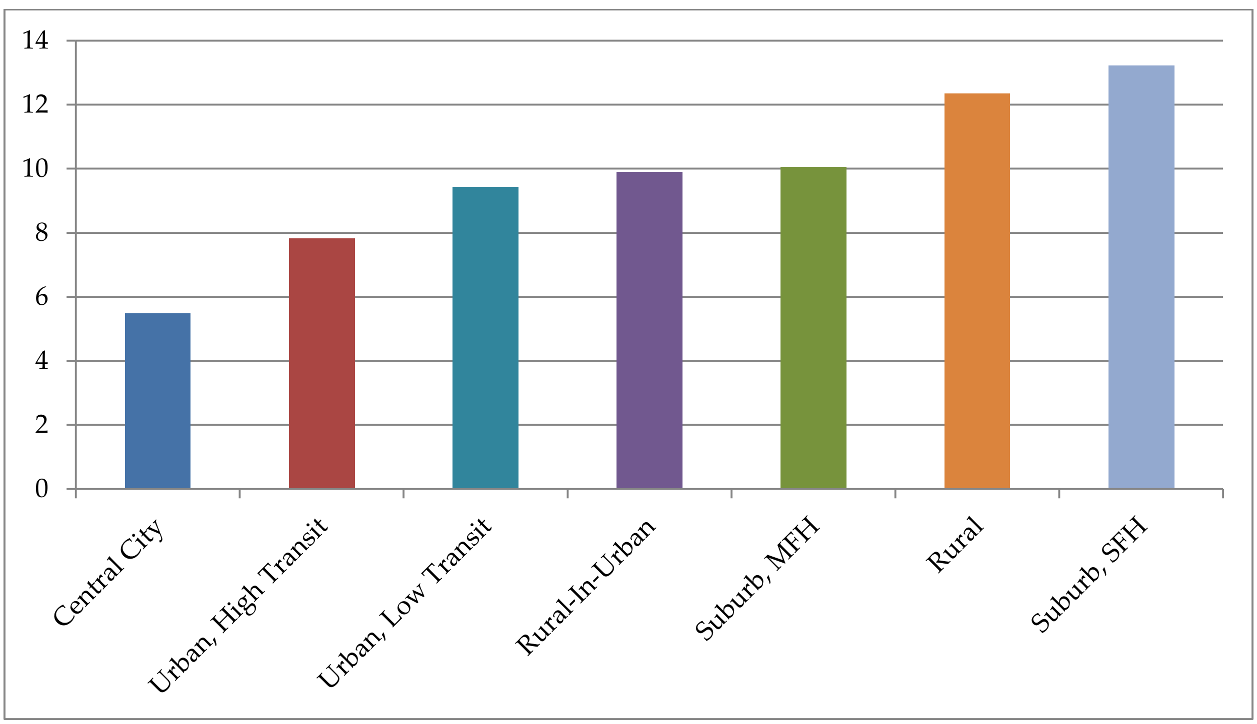

Figure 9: Average Individual Home-to-Work Commute VMT by Neighborhood Type

Empirical Estimation Approach

The research goal of this project was to explore heterogeneity in how much Californians will change the amount that they drive in response to changes in land use and transport system characteristics. We focus especially on the effect of variables that local and regional policy makers have some control over. We explore heterogeneity across two important dimensions – neighborhood type and trip type. We control for key household and individual demographic characteristics such as income and household type, as well as characteristics of the surveys themselves such as the day of the week, the season of the year, and the region of the state where the survey was conducted. We also control for household selection of residential neighborhood type. We use the software package Stata to perform all of our statistical data analysis.

Estimating a statistical model of VMT is difficult for two reasons. First, a common concern in statistical estimation of the relationship between land use and travel choices is residential self-selection. Do associations reflect the impact of land use on travel, or do associations reflect that persons choose to live in neighborhoods with land use patterns that support their desired travel behavior? In cross-sectional data that does not include attitudinal variables (such as travel diary surveys), it is not possible to know the difference. To the extent that people choose to live in neighborhoods based on their travel preferences, land use characteristics of a neighborhood are actually endogenous variables in a model of VMT. In other words, people are jointly choosing how much they want to drive and the land use characteristics of their neighborhood, which means that we can't obtain clean estimates of the effect of land use characteristics on VMT with a direct regression model. If this is not accounted for in the estimation method, estimated coefficients and calculated marginal effects and elasticities may be biased.

Second, there are a significant number of observations that have zero VMT on their assigned travel survey day. Some of these households/people simply did not leave home that day, while others made trips using exclusively transport modes other than the car. Regardless of the reason, estimating a linear statistical model when the dependent variable includes a high percentage of zeroes skews the estimated variable coefficients.

Readers who are not interested in the details of how these statistical challenges were addressed in this research can now skip to the next section, with the understanding that steps were taken in the analysis to address them. It is not necessary to understand the details of these models to interpret the estimated elasticities and marginal effects reported here. These can be interpreted directly and directly compared to reported estimates of similar results in the existing literature. The remainder of this section is a more technical account of our application of empirical methods to address these statistical challenges.

Technical Estimation Details

To surmount the first of these statistical challenges, we employed a two-step approach in which the first step was to estimate a multinomial logit model of household choice of residential neighborhood type, and the second step was to estimate a model of VMT that includes selection variables that are based on the predicted probabilities of each neighborhood type from the multinomial logit model. Inclusion of these selection variables corrects for the fact that households select neighborhood type at least partially based on how far they want to drive.

This method results in estimation of separate models of VMT for each neighborhood type, with corresponding separate estimated coefficients, marginal effects, and elasticities.

Our method follows that used in the seminal 1984 paper that controlled for appliance choice in a model of household energy use (Dubin and McFadden). As such, the selection variables included in the models of VMT are calculated as follows:

$$Selection_{i_j} | i \neq j = \frac{P_j * \ln(P_j)}{(1 - P_j)} + \ln(P_i)$$

where *i* indicates the chosen neighborhood type and *j* indexes the not-chosen neighborhood types, and the predicted probability of choosing neighborhood type *k* based on the multinomial logit model is $P_k = \frac{\exp(z\gamma_k)}{\sum_l \exp(z\gamma_l)}$. Note that this formulation means that the selection variables appearing in our models of VMT are actually a different set of variables in each model. It is not necessary to interpret the coefficients on these selection variables. They are meant to control for household selection of neighborhood type so that the coefficients and associated estimates of elasticities and marginal effects of the remaining variables can be interpreted as closer to the direct effects of socioeconomic and land use characteristics on VMT for each neighborhood type.

To address the statistical challenge presented by the large number of zero VMT observations, we employ a tobit model specification for our models of VMT. The tobit is usually discussed in the context of a censored dependent variable, but is also appropriate when the dependent variable takes the value of zero as a "corner solution" for a significant percentage of observations in a dataset (Woolridge, 2002), as is our case. The tobit framework is that the main dependent variable (in our case, VMT) is equal to some continuous latent variable when that latter variable takes a positive value, and equals zero when that latent variable is zero or negative. The tobit model is based on the censored normal distribution for the observed data, and uses a maximum likelihood estimation procedure to estimate the uncensored latent variable, usually denoted as Y^*. More details on either the basic multinomial logit or the tobit models are readily available in most econometrics textbooks.

To account for the fact that some households in our estimation sample have more than one adult and/or recorded their VMT on more than one day, we account for the correlation among household member travel by clustering the standard errors of our estimates by household.

The model goodness of fit measures that we report are McFadden's Pseudo-R2 for the multinomial logit model and a measure suggested by Veall and Zimmerman (1994) for the tobit model, which they call R^2_{MZ1} and is given by the following equation.

$$R^2_{MZ1} = \frac{\sum_{i=1}^{N}(\hat{Y}_i^* - \overline{\hat{Y}_i^*})}{\sum_{i=1}^{N}(\hat{Y}_i^* - \overline{\hat{Y}_i^*}) + N\hat{\sigma}^2}$$

where $\hat{Y}_i^*$ is the predicted value of the dependent variable, $\overline{\hat{Y}_i^*}$ is the average of the predicted value of the dependent variable, *N* is the number of observations, and $\hat{\sigma}$ is the estimated value from the tobit model. This measure of R^2 for the tobit has two desirable properties: it ranges from 0 to 1 and it is equal to the ordinary least squares R^2 in the case where there are not observations with zero VMT.

Choice of Explanatory Variables

Our chief interest is in understanding the effect on VMT of variables that are policy-sensitive such as land use and transportation system characteristics. How many miles are driven by a person is determined by a combination of the number of trips, the average trip distance, and trip mode choices. The explanatory variables included in our analyses are all expected to affect one or more of these factors. Included variables represent a variety of land use and transport system characteristics that are expected to directly affect these factors, as well as controls for relevant individual, household, and survey characteristics.

For instance, higher levels of local job access and higher levels of activity mix should mean that commute and some personal business trips are relatively short in that census tract. These land use characteristics may also be associated with higher trip frequencies, since each trip is less onerous (e.g. commuters may be more likely to go home for lunch if they live around the corner from their work location). Higher road density may reduce average trip length by providing more direct routes. Higher transit and nonmotorized mode use for commuting serve as indicators that alternatives to the private car are available in a census tract, and likely relate to lower VMT because some people would use these alternatives.

In selecting policy-sensitive land use and transportation system variables to include in the analysis, we faced the challenge that many are highly correlated with each other. While this multicollinearity does not lead to biased estimates per se, it can result in misleading estimated parameters and also to reduced statistical significance of those parameters.

Table 18 reports the correlations between the land use variables that we use in our final empirical specification. In this set of land use variables, the highest correlation is between local job accessibility and the percent of commuters who use transit in that census tract.

One variable that is commonly important in existing studies of VMT and that is noticeably absent from our main analyses is population density. There are two main reasons for this. First and most importantly, we do not expect population density to have a large direct effect on VMT. Higher residential densities may make trips to visit friends and family shorter, but do nothing to directly affect the distances traveled for other purposes. It is because population density is highly correlated with variables such as road density, job access, percent single family homes, and transit use that this variable is often included in analyses of VMT. However, because we included these variables that more directly impact VMT in our analyses, we found that population density was not a statistically significant predictor of VMT for most of our regressions. Further, because it is so highly correlated with variables that we do include, we found that including population density reduced the magnitude of our estimated effects for some of these other variables. Road density was the most affected variable.

A number of built environment variables in addition to population density were tested and ultimately not included in our final models. There were three basic reasons that variables were rejected. First, some variables were statistically insignificant when included in our analyses. These included population density (discussed above), restaurants within walking/driving distance, and retail density. Second, improved versions of other variables were created. The main variable in this category was job accessibility. As discussed earlier in this report, a number of versions of job accessibility were tested before arriving at our final specification of "local" and "regional" accessibility. Third, the theoretical link between the variable and VMT was sufficiently weak that including it in the analysis would not be helpful for policy, and could be misleading. The variables in this category were those relating to the age of the housing stock in a census tract.

In choice of control variables to include, we were somewhat limited by the fact that we could only use variables that were available in all five of the travel surveys that form our dataset. The survey characteristics included are the day of the week, the region of the state, and the season of the year when the survey was conducted. We decided not to also control for the survey year because doing so causes us not to be able to estimate the coefficient on our gasoline price variable – gas price is highly correlated with year. This means that to the extent that there is a change in VMT over time that is not explained by changes over time in the variables used in our analysis, we are not properly accounting for this.

Table 18: Correlations between Census Tract-Level Land Use Explanatory Variables Used in Analysis

	Percent Transit	Local Job Access (0-5 miles)	Regional Job Access (5-50 miles)	Activity mix	Percent Walk/Bike	Road Density	Percent SFH
Percent Transit	1.00						
Local Job Access (0-5 miles)	0.65	1.00					
Regional Job Access (5-50 miles)	0.26	0.51	1.00				
Activity mix	-0.04	0.11	-0.05	1.00			
Percent Walk/Bike	0.31	0.39	-0.01	0.21	1.00		
Road Density	0.42	0.55	0.45	-0.05	0.13	1.00	
Percent SFH	-0.46	-0.49	-0.19	-0.23	-0.37	-0.36	1.00

In our household VMT analysis, we control for the household-level characteristics of income, household size, number of vehicles owned, number of workers, and life stage. In our analyses of commute and nonwork VMT that use individual adults as the unit of analysis, we add individual characteristics as control variables. All of these household and individual characteristics are likely to have an effect on one or more of the three factors that determine VMT: number of trips, average trip distance, and trip mode.

Note that distances to key destinations such as work and school are not included as explanatory variables in the model of household VMT. Although including these variables certainly would improve the overall model fit, doing so would obscure the relationship between the built environment and VMT. This is because a large part of the relationship between the built environment and VMT is the effect of land use characteristics on the distance to work and school. Including actual distances to work and school in the model ends up controlling for that part of the relationship, and therefore obscuring the relationships we care about between land use variables and household VMT.

Marginal Effects and Elasticities

The main useful results of the analysis reported on here are actually estimated marginal effects and elasticities of the included land use and transport system variables. Marginal effects are interpreted as the change in the dependent variable when an explanatory variable changes by one unit.

Marginal effects from a tobit model can be calculated in three ways (see Greene 1997, Chapter 20). For this analysis, we use the most common of these which is given by the following expression:

$$Marginal\ Effect\ of\ variable\ x\ for\ observation\ i = \frac{\partial E[y_i|x_i]}{\partial x_i} = \beta\Phi(\frac{\beta' x_i}{\sigma})$$

where $E[y_i|x_i]$ is the predicted value of the censored dependent variable (in our case, VMT), β is the vector of estimated tobit coefficients, and $\Phi(\frac{\beta' x_i}{\sigma})$ is the cumulative normal distribution for the predicted value of the latent variable Y^* divided by the estimated parameter σ.

The tobit model takes into account both the probability that a particular observation may be censored (i.e. have zero VMT) and the determinants of the value of the dependent variable for uncensored observations (i.e. nonzero VMT). The marginal effects from the tobit model can be decomposed into these two effects, following McDonald and Moffit (1980). In our tables of marginal effects, we indicate the fraction of the reported effects for each analysis that is due to the effect of the variable on the probability of VMT being nonzero and that is due to the effect of the variable conditional on VMT being above zero.

In using marginal effects, it is important to take note of the units of the explanatory variable. In the analysis presented here, most of the variables are scaled so that they all have similar ranges. This means that a one unit change for some variables is actually a very large change, while a one unit change for other variables is small. That said, the advantage of using marginal effects for policy analysis is that as long as the units are clearly understood, the marginal effects are also easy to understand and use for scenarios.

Another way to represent the effect of explanatory variables on VMT is in terms of elasticities. An elasticity is the percent change in the dependent variable when an explanatory variable changes by one percent. Elasticities avoid the scaling problem that is present for marginal effects by evaluating percent changes. However, elasticities for individual observations are usually widely variable across any particular dataset, so we report the mean of these individual elasticities here. While these percentage change effects are therefore robust for more average values of the explanatory variables, they can be quite inaccurate for other values of these variables. That said, when comparing to the existing literature, elasticities are an easier point of comparison than marginal effects because the units of measurement of the variables do not need to be taken into account.

VMT Impact Spreadsheet Tool Development

Part of this project is to develop a spreadsheet tool that will allow the research findings from this project to be applied across the state in local government policymaking. The VMT Impact spreadsheet tool allows users to select a jurisdiction (city, county, or region) or even an individual census tract, and to learn what the findings of this research are for the particular area of the state. Here, we briefly describe what is included in the tool, and describe how decision makers can use it to inform their policy choices.

The VMT Impact spreadsheet tool was created using Microsoft Excel spreadsheet software, and is based on a relatively simple set of lookup tables. The tool has base data for all of the census tracts in California embedded in it, including the neighborhood type designation and the main land use and transportation system characteristic variables that we report on in our model of VMT. This data about each census tract is linked to the tract's home region, county, and, where applicable, also to its home city. The tool also has our main research results embedded in it in terms of marginal effects and elasticities of land use and transport system variables.

When users select a jurisdiction of interest, they can quickly see the jurisdiction-level effects on the main results worksheet, displayed as the lower and upper boundaries of 95% confidence intervals. If the user is interested in looking deeper into a particular neighborhood, he or she can do so by identifying the particular census tracts that are in that neighborhood and looking at the results at the tract level on the tract results worksheet.

The tool is designed to be user-friendly, even for those who are not advanced spreadsheet users. In contrast to many existing sketch planning tools that produce VMT estimates, this tool provides only information about the effects of changes in the land use and transport system on VMT. An advantage to the VMT Impact tool is that it is extremely simple and straightforward, and does not produce results that emerge from a "black box".

We hope that this VMT Impact spreadsheet tool will be a useful way to share the results of this research with those making real-world policy decisions, and that in this way we can help to inform more targeted local policies throughout the state.

RESULTS

The results of this research are divided into three analyses: one that looks at the determinants of household daily VMT, one that looks at individual commute VMT, and a third that looks at individual non-work VMT. The details of our methodology are in the previous section of this report, and a full discussion of the implications of our results for policy are in the following section. Here, we report the actual results tables for each empirical estimation, highlight important points about the process of arriving at these final specifications of the models of VMT, and discuss model characteristics such as overall goodness of fit.

For each of our analyses, we present three tables of results. The first of these reports the estimated tobit coefficients for all of the independent and control variables included in the analysis, the second reports estimated marginal effects of a few demographic control variables and the full set of land use and transportation system characteristics included in the analyses, and the third reports estimated elasticities for these same variables. For each point estimate in all of the results tables, we provide its 95% confidence interval below the estimate.

Each table of VMT results is divided into 8 columns. The first column reports the estimated tobit results for an analysis of the full dataset that does not use sample selection to control for residential self selection (RSS). The remaining seven columns report results for models of VMT in each neighborhood type in turn, as indicated in the column headers, each including selection variables derived from the MNL model of neighborhood type choice to control for residential self selection.

At the bottom of each column of the tables, we also list additional information about each of the estimations. All of the tables include the total number of observations that the estimated results are based on, the number of observations that were zero VMT, and the R^2 goodness-of-fit measure for that model. In the tables of marginal effects, we also include a decomposition of the marginal effect into the portion that is conditional on the VMT being above zero, and the portion that is the effect on the probability of the VMT being above zero.

Household Weekday VMT

For policy purposes, we expect that the most important set of results will be those that identify the impact of policy-sensitive variables on total household VMT. Although it is interesting and useful to know more about commute VMT and nonwork VMT, it is reducing total household VMT that is important for reducing greenhouse gas emissions from travel.

For this analysis, the dependent variable is the sum of the distances for all trips taken by household members in private vehicles on the travel diary day. A trip was counted as contributing to the total household VMT whether the person was a driver or a passenger. However, when household members reported taking trips together in the same vehicle, the trip is counted only once. Only households that fully completed the travel diary are included in this estimation, including the location of the origins and destinations for all personal vehicle trips.

Table 19 presents our multinomial logit estimation results for our neighborhood type selection model, Table 20 presents our tobit estimation results, Table 21 presents the associated marginal effects for policy-sensitive variables, and Table 22 presents the mean of the calculated individual elasticities for these same variables.

The goodness of fit measure that we report for the tobit models of household VMT ranges from 0.23 to 0.46, which is considered reasonable to excellent for disaggregate models of travel behavior. When compared to ordinary least squares regressions on the same data (not shown), the tobit goodness of fit measures are higher, suggesting that this empirical specification explains VMT better. Looking at the decomposition of the tobit marginal effects, it is apparent that while there is some variation, most of the models have marginal effects that are approximately half due to the effect of the variables on the probability of VMT being nonzero and half due to the effect of the variables on VMT, conditional on VMT being above zero.

Individual Nonwork VMT

In addition to modeling full household VMT, we look specifically at how land use and transport system variables impact two categories of trip type: nonwork trips and home-to-work commute trips. In these analyses, we look at individuals instead of full households as the unit of analysis.

The dependent variable in the nonwork trip analysis is the sum of the distances of all non-work trips taken in private vehicles reported by an individual 16 years or older on the travel diary day. As for household VMT, a trip was counted as contributing to total nonwork VMT whether the person was a driver of a passenger. Trips were assigned to the non-work category if they had both an origin and a destination that was not identified as a work location by the respondent, and if the trip was not identified by the respondent to be work-related in some way. Only individuals that fully completed the travel diary are included in this estimation, including the location of the origins and destinations for all personal vehicle trips.

Individuals who had zero nonwork VMT either because they did not travel at all on the travel diary day or because they traveled only for work or school-related purposes are left out of this analysis. The reason for this is that including these people in the model results in estimated coefficients that are much less clear to interpret because the coefficients are trying to explain why people zeroes in the dependent variable that have widely different implications. Those who remain with zero nonwork VMT are those who actually did make nonwork trips, but used only alternatives to the private vehicle to make those trips.

Table 23 presents our tobit estimation results, Table 24 presents the associated marginal effects for policy-sensitive variables, and Table 25 presents the mean of the calculated individual elasticities for these same variables. Our multinomial logit estimation results for our neighborhood type selection model are extremely similar to those presented in Table 19, and are not separately included here.

The goodness of fit measure that we report for the tobit models of individual nonwork VMT ranges from 0.08 to 0.30. When compared to ordinary least squares regressions on the same data (not shown), the tobit goodness of fit measures are higher, suggesting that this empirical specification explains VMT better. Looking at the decomposition of the tobit marginal effects, it is apparent that while there is some variation, most of the models have marginal effects that are approximately half due to the effect of the variables on the probability of VMT being nonzero and half due to the effect of the variables on VMT, conditional on VMT being above zero.

Individual Adult Home-To-Work Commute VMT

The dependent variable here is the one-way commute distance between a respondent's home and workplace or school. We considered using total work-related VMT instead of focusing on the one way commute, but the difficulty of consistently assigning commute purpose VMT to multi-leg travel tours proved to be beyond the scope of this project. Only individuals who traveled directly from their home to their workplace or from their workplace to their home on the travel diary day were included in this estimation.

For this analysis, those with zero home-to-work commute VMT fall into two categories: telecommuters and alternative mode commuters. Observations in our analysis with zero home-to-work VMT compose approximately 10% of the total.

Table 26 presents our tobit estimation results, Table 27 presents the associated marginal effects for policy-sensitive variables, and Table 28 presents the mean of the calculated individual elasticities for these same variables. Our multinomial logit estimation results for our neighborhood type selection model are extremely similar to those presented in Table 19, and are not separately included here.

The goodness of fit measure that we report for the tobit models of individual home-to-work commute VMT ranges from 0.08 to 0.66. When compared to ordinary least squares regressions on the same data (not shown), the tobit goodness of fit measures are higher, suggesting that this empirical specification explains VMT better.

Summary Results Tables by Neighborhood Type

Table 29 through Table 35 report the same marginal effect and elasticity results as the main results tables described above, but are organized by neighborhood type so that readers can see all of the results in one table for a particular neighborhood type.

Table 19: Multinomial Logit Model of Neighborhood Type Choice, Estimated Coefficients for Household VMT Model

INDEPENDENT VARIABLES	Urban Low Transit Use	Suburb MFH	Central City	Rural	Urban High Transit Use	Rural In Urban
Number of Vehicles	-0.202*** (-0.237 to -0.166)	-0.190*** (-0.223 to -0.156)	-2.045*** (-2.223 to -1.867)	0.138*** (0.101 to 0.175)	-0.822*** (-0.892 to -0.753)	-0.0335 (-0.0887 to 0.0216)
Income ($10,000)	-0.0256*** (-0.0423 to -0.00899)	-0.124*** (-0.140 to -0.108)	0.184*** (0.136 to 0.231)	-0.217*** (-0.239 to -0.195)	-0.115*** (-0.140 to -0.0908)	-0.206*** (-0.235 to -0.177)
Income Sq. ($10,000)	0.000735** (0.000163 to 0.00131)	0.00260*** (0.00201 to 0.00319)	-0.00439*** (-0.00611 to -0.00266)	0.00569*** (0.00491 to 0.00647)	0.00328*** (0.00240 to 0.00416)	0.00505*** (0.00399 to 0.00611)
Number of Workers	0.0379* (-0.00543 to 0.0811)	0.0964*** (0.0545 to 0.138)	0.397*** (0.242 to 0.551)	-0.0575** (-0.112 to -0.00258)	0.285*** (0.218 to 0.352)	-0.0521 (-0.124 to 0.0200)
Homeowner	-0.749*** (-0.821 to -0.677)	-0.718*** (-0.788 to -0.648)	-1.957*** (-2.163 to -1.751)	-0.244*** (-0.340 to -0.147)	-1.131*** (-1.227 to -1.034)	-0.478*** (-0.592 to -0.364)
White Household	-0.232*** (-0.354 to -0.110)	-0.228*** (-0.346 to -0.110)	0.186 (-0.197 to 0.570)	-0.233*** (-0.377 to -0.0899)	-0.266*** (-0.445 to -0.0864)	-0.274*** (-0.456 to -0.0926)
Hispanic Household	0.293*** (0.148 to 0.438)	0.330*** (0.191 to 0.469)	-0.310 (-0.804 to 0.183)	0.0684 (-0.106 to 0.243)	0.450*** (0.251 to 0.650)	0.135 (-0.0808 to 0.351)
Asian Household	0.206*** (0.0502 to 0.362)	0.152* (-0.00593 to 0.310)	0.464** (0.00338 to 0.926)	-1.031*** (-1.291 to -0.770)	0.488*** (0.269 to 0.707)	-0.987*** (-1.321 to -0.653)
Black Household	0.376*** (0.202 to 0.550)	0.660*** (0.496 to 0.824)	0.273 (-0.247 to 0.793)	-0.141 (-0.372 to 0.0905)	1.094*** (0.873 to 1.315)	-0.109 (-0.396 to 0.177)
San Diego/ Sacramento	-0.661*** (-0.740 to -0.582)	0.483*** (0.418 to 0.549)	-1.335*** (-1.623 to -1.047)	-0.154*** (-0.264 to -0.0444)	-1.213*** (-1.351 to -1.076)	-0.140* (-0.288 to 0.00768)
Central Valley/ Central Coast	-4.628*** (-5.174 to -4.081)	0.0325 (-0.0507 to 0.116)	-18.18*** (-18.31 to -18.05)	0.964*** (0.871 to 1.058)	-19.15*** (-19.23 to -19.08)	0.839*** (0.717 to 0.961)
Rural CA	-20.88*** (-21.01 to -20.75)	-0.403*** (-0.632 to -0.175)	-19.58*** (-19.80 to -19.36)	3.350*** (3.206 to 3.495)	-20.57*** (-20.72 to -20.42)	2.765*** (2.594 to 2.936)
Youngest Child 0-5	-0.313*** (-0.410 to -0.217)	-0.251*** (-0.344 to -0.159)	-1.147*** (-1.598 to -0.696)	-0.0710 (-0.195 to 0.0528)	-0.606*** (-0.751 to -0.462)	0.0804 (-0.0718 to 0.233)
Youngest Child 6-17	-0.449*** (-0.536 to -0.361)	-0.276*** (-0.357 to -0.195)	-1.531*** (-1.982 to -1.081)	-0.119** (-0.226 to -0.0127)	-0.620*** (-0.752 to -0.489)	-0.128* (-0.270 to 0.0145)
Senior	-0.0394	-0.184***	-0.413***	-0.0505	-0.586***	0.0518

INDEPENDENT VARIABLES	Urban Low Transit Use	Suburb MFH	Central City	Rural	Urban High Transit Use	Rural In Urban
Household	(-0.129 to 0.0504)	(-0.268 to -0.0990)	(-0.704 to -0.122)	(-0.158 to 0.0567)	(-0.731 to -0.442)	(-0.0850 to 0.189)
Constant	0.907***	1.148***	-0.0264	-0.317***	1.458***	-0.521***
	(0.760 to 1.055)	(1.007 to 1.289)	(-0.441 to 0.388)	(-0.495 to -0.138)	(1.255 to 1.660)	(-0.744 to -0.297)
Observations: 53,608						
Pseudo R-squared (Household VMT model): 0.136						

Robust 95% Confidence Intervals in Parentheses below Point Estimates

*** p<0.01, ** p<0.05, * p<0.1

Note that the base neighborhood type choice alternative is Suburb with Single Family Housing, Los Angeles/San Francisco is the comparison region, and adults under 65 with no children is the comparison household type.

Table 20: Tobit Estimated Coefficients for Model of Weekday Household VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
($10,000)	(3.357 to 3.931)	(0.357 to 3.025)	(2.411 to 5.444)	(-2.820 to 6.465)	(1.790 to 6.521)	(3.041 to 5.938)	(-0.888 to 3.071)	(-1.152 to 5.580)
Income Sq. ($10,000)	(-0.114 to - 0.0934)	-0.0496*** (-0.0840 to - 0.0152)	-0.112*** (-0.152 to - 0.0707)	-0.0321 (-0.155 to 0.0912)	-0.141*** (-0.208 to - 0.0745)	-0.125*** (-0.163 to - 0.0869)	-0.0598** (-0.115 to - 0.00501)	-0.0619 (-0.164 to 0.0403)
Number of Workers	12.05*** (11.16 to 12.94)	12.38*** (10.47 to 14.29)	12.73*** (10.68 to 14.79)	5.732 (-3.082 to 14.55)	16.87*** (13.73 to 20.01)	13.40*** (11.69 to 15.11)	11.51*** (7.076 to 15.94)	16.51*** (12.16 to 20.86)
Household Size	5.500*** (4.331 to 6.668)	4.648*** (2.499 to 6.797)	6.319*** (4.084 to 8.554)	-3.599 (-15.56 to 8.365)	8.050*** (4.185 to 11.91)	7.656*** (5.430 to 9.881)	-1.519 (-4.738 to 1.700)	4.360 (-1.327 to 10.05)
Spring or Summer	6.480*** (5.389 to 7.570)	4.671*** (2.702 to 6.641)	7.412*** (5.047 to 9.778)	-0.265 (-7.060 to 6.530)	11.75*** (7.761 to 15.74)	6.002*** (4.036 to 7.967)	1.631 (-1.498 to 4.760)	9.400*** (3.663 to 15.14)
Local Gasoline Price (cons. $)	(-3.086 to -	-2.363*** (-3.760 to -0.965)	-2.236*** (-3.592 to - 0.879)	5.164 (-2.604 to 12.93)	-1.133 (-3.579 to 1.312)	-2.680*** (-3.894 to - 1.466)	-3.450*** (-6.025 to -0.874)	-2.429
Transit Access (census-based)	-0.353*** (-0.444 to - 0.263)	-0.236 (-0.588 to 0.116)	-0.626*** (-0.930 to - 0.323)	-0.478** (-0.929 to - 0.0273)	-0.791 (-1.947 to 0.365)	-0.437*** (-0.717 to - 0.157)	-0.384*** (-0.606 to -0.161)	-1.444*** (-2.455 to - 0.433)
Jobs Access 0-5 miles, grav.	(-0.697 to -	-0.616*** (-0.827 to -0.405)	-1.413*** (-1.835 to - 0.991)	-0.114 (-0.586 to 0.359)	-3.186** (-5.928 to - 0.444)	-3.004*** (-3.590 to - 2.418)	-0.135 (-0.432 to 0.162)	-1.819* 0.213)
Jobs Access 5-50 miles, grav.	0.0797* (-0.00791 to 0.167)	-0.437*** (-0.767 to -0.107)	0.314*** (0.103 to 0.526)	-2.454 (-6.703 to 1.795)	2.687*** (1.839 to 3.535)	0.240* (-0.0145 to 0.494)	0.262 (-0.439 to 0.963)	2.361*** (1.183 to 3.538)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
(census-based)	(-0.376 to -0.154)	(-0.186 to 0.191)	(-0.258 to 0.171)	(-0.594 to 0.378)	(-0.549 to 0.408)	(-0.936 to -0.302)	(-0.608 to -0.0748)	(-0.644 to 0.146)
Road Density	(-1.025 to -	-0.257* (-0.546 to 0.0309)	-0.645*** (-1.007 to -0.282)	0.341 (-0.974 to 1.656)	-1.647*** (-2.530 to -0.764)	-0.522*** (-0.781 to -0.262)	-0.171 (-0.642 to 0.300)	-0.735
Perc. Single Family Homes	0.0279** (0.00423 to 0.0516)	-0.0167 (-0.0634 to 0.0300)	-0.0293 (-0.0832 to 0.0247)	0.560 (-0.385 to 1.506)	0.195*** (0.0747 to 0.315)	0.0701** (0.00692 to 0.133)	-0.0669 (-0.151 to 0.0167)	0.145* (-0.0182 to 0.309)
SACOG	(2.965 to	N/A	6.364 36.71)	N/A	16.02 64.46)	31.63** (1.429 to 61.83)	N/A	-87.60** 11.66)
SF Bay Area	15.00*** (12.22 to 17.77)	-12.77 (-35.11 to 9.569)	10.20 (-19.26 to 39.66)	N/A	1.692 (-45.10 to 48.49)	36.07** (4.968 to 67.18)	-71.81** (-142.6 to -0.997)	-74.35* (-157.1 to 8.356)
Central Coast	(2.472 to	71.02** (3.278 to 138.8)	17.13 (-10.42 to 44.67)	N/A	29.87* 62.35)	37.39*** (12.36 to 62.41)	N/A	-30.13
Central Valley	4.484*** (1.343 to 7.625)	65.75** (11.28 to 120.2)	17.54 (-7.274 to 42.35)	N/A	24.34 (-8.306 to 56.98)	32.48*** (8.273 to 56.69)	N/A	-34.60 (-84.85 to 15.64)
Mountains	(-9.266 to 3.546)	N/A	N/A	N/A	-2.371 (-10.05 to 5.305)	-30.39*** (-51.31 to -9.470)	N/A	-26.59*** (-41.02 to -12.16)
SCAG	13.04*** (9.873 to 16.21)	-3.376 (-27.09 to 20.34)	6.942 (-22.22 to 36.11)	68.36 (-22.13 to 158.9)	1.955 (-43.95 to 47.86)	33.04** (2.004 to 64.07)	-76.02** (-148.8 to -3.221)	-79.89* (-161.1 to 1.347)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
	(1.504 to 4.178)	(-0.643 to 4.238)	(-1.618 to 3.948)	(-9.078 to 4.808)	(-1.278 to 8.874)	(0.482 to 5.175)	(-0.590 to 6.766)	(5.054 to 19.96)
Wednesday	(2.030 to	4.790*** (2.081 to 7.498)	1.500 (-1.561 to 4.560)	4.355 (-4.059 to 12.77)	0.822 (-4.637 to 6.281)	3.721*** (1.184 to 6.259)	3.742* (-0.257 to 7.742)	9.754**
Thursday	3.047*** (1.555 to 4.539)	3.378** (0.542 to 6.214)	2.122 (-0.993 to 5.238)	3.256 (-5.378 to 11.89)	0.121 (-5.250 to 5.492)	3.218** (0.561 to 5.875)	4.686* (-0.0229 to 9.396)	8.280** (0.961 to 15.60)
Friday	(2.913 to	4.305*** (1.458 to 7.151)	1.602 (-1.641 to 4.846)	9.029** (0.0441 to 18.01)	5.232* (-0.197 to 10.66)	6.181*** (3.391 to 8.972)	1.596 (-2.633 to 5.824)	11.49***
2+Adults <64, no kids	-0.907 (-2.783 to 0.968)	-4.688*** (-8.073 to -1.304)	-4.803** (-8.464 to -1.141)	1.912 (-13.06 to 16.88)	-2.948 (-9.580 to 3.685)	-1.628 (-5.393 to 2.137)	-0.254 (-5.508 to 4.999)	-1.110 (-10.43 to 8.216)
1 adult Child 0-5	(-1.641 to	5.774 (-6.760 to 18.31)	-0.859 (-9.758 to 8.040)	113.5*** (79.42 to 147.7)	-4.863 (-26.47 to 16.74)	4.062 (-9.272 to 17.40)	24.47* (-2.406 to 51.34)	9.892
2+ adults Child 0-5	8.369*** (4.425 to 12.31)	7.555* (-0.556 to 15.67)	1.399 (-6.500 to 9.298)	45.81** (10.29 to 81.33)	-5.011 (-18.64 to 8.617)	8.138** (0.234 to 16.04)	20.32*** (5.726 to 34.92)	6.500 (-12.66 to 25.66)
1 adult Child 6-17	(0.903 to	-0.668 (-7.830 to 6.494)	3.759 (-3.065 to 10.58)	39.96** (5.716 to 74.21)	-0.490 (-12.43 to 11.45)	2.487 (-4.086 to 9.060)	12.36** (0.610 to 24.11)	3.641 17.14)
2+ adults Child 6-17	6.189*** (2.438 to 9.940)	1.722 (-5.369 to 8.813)	-0.650 (-8.681 to 7.382)	26.40 (-15.68 to 68.49)	1.468 (-11.10 to 14.04)	7.825** (0.749 to 14.90)	21.79*** (7.721 to 35.87)	-2.324 (-21.82 to 17.17)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
2+ adults >64 No kids	-4.878*** (-7.176 to - 2.580)	-6.349** (-11.70 to -0.999)	-6.807*** (-11.93 to - 1.689)	13.70 (-21.23 to 48.63)	-12.60*** (-20.35 to - 4.847)	-9.186*** (-13.99 to - 4.386)	5.307 (-7.940 to 18.55)	-6.388 (-18.14 to 5.364)
Selection Variable Urban Low Transit Use	N/A	N/A	(-112.1 to - 34.67)	46.91 (-174.1 to 267.9)	-59.21 (-135.2 to 16.79)	-62.46*** (-104.2 to - 20.76)	-172.6*** (-254.9 to -90.22)	-114.7** (-212.2 to -
Selection Variable Suburb MFH	N/A	14.03 (-33.79 to 61.85)	N/A	-71.10 (-314.7 to 172.5)	50.81** (7.738 to 93.88)	-1.724 (-34.41 to 30.96)	93.57 (-48.72 to 235.9)	-20.31 (-76.16 to 35.53)
Selection Variable Central City	N/A	27.02*** (10.14 to 43.90)	(35.70 to	N/A	90.00*** 145.6)	58.26*** (34.40 to 82.12)	61.79*** (39.21 to 84.37)	131.3*** 211.5)
Selection Variable Rural	N/A	-64.49 (-174.0 to 45.04)	-87.39** (-162.8 to - 11.95)	-372.2 (-1,162 to 417.6)	N/A	-118.4*** (-195.3 to - 41.41)	-116.6 (-343.5 to 110.3)	32.81 (-79.99 to 145.6)
Selection Variable Suburb SFH	N/A	-9.515 (-26.81 to 7.780)	(-23.95 to 11.01)	0.467 (-92.65 to 93.58)	-18.65 (-54.04 to 16.73)	N/A	-7.764 (-57.59 to 42.06)	-37.97 (-86.69 to 10.76)
Selection Variable Urban High Transit Use	N/A	9.062 (-16.47 to 34.59)	12.38 (-6.591 to 31.35)	-38.15 (-145.5 to 69.23)	-22.40 (-63.28 to 18.49)	0.617 (-24.74 to 25.97)	N/A	4.748 (-46.08 to 55.58)
Selection Variable Rural-In-Urban	N/A	52.86 (-90.74 to 196.5)	104.0** (12.28 to 195.8)	442.4 (-410.8 to 1,296)	-36.26 (-107.8 to 35.23)	121.6** (26.29 to 216.8)	148.2 (-117.1 to 413.6)	N/A
Constant	-16.60*** (-20.73 to - 12.47)	70.28*** (21.16 to 119.4)	-25.21 (-60.99 to 10.57)	-21.15 (-104.4 to 62.05)	-38.73** (-75.10 to - 2.363)	-69.62*** (-115.3 to - 24.00)	54.36 (-76.81 to 185.5)	-18.61 (-129.2 to 91.95)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Sigma	54.01*** (52.93 to 55.09)	44.90*** (43.13 to 46.67)	51.22*** (48.49 to 53.96)	39.27*** (35.50 to 43.03)	64.19*** (60.56 to 67.82)	56.75*** (55.01 to 58.48)	44.34*** (41.28 to 47.40)	60.61*** (55.24 to 65.98)
Observations	53,608	10,122	11,734	1,093	5,712	17,846	4,581	2,520
Observations with Zero VMT	7,729	1,230	1,737	517	1,061	1,537	1,187	460
R2: MZ1	0.269	0.234	0.256	0.458	0.229	0.246	0.307	0.235

Robust 95% Confidence Intervals in Parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note that Monday is the comparison day of the week, Northern CA is the comparison region, and single adult is the comparison life stage. Selection variables are derived from the multinomial logit model predicted probabilities of residential neighborhood type choice.

Table 21: Tobit Marginal Effects for Model of Weekday Household VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
($10,000)	(1.347 to 1.549)	(0.0323 to 1.235)	(1.022 to 2.459)	(-0.676 to 1.822)	(0.588 to 2.847)	(1.064 to 2.244)	(-0.715 to 1.058)	(-0.540 to 2.570)
	(8.270 to 9.583)	(8.055 to 10.97)	(7.757 to 10.72)	(-1.439 to 6.828)	(9.813 to 14.24)	(9.372 to 12.11)	(4.522 to 10.12)	(8.340 to 14.20)
Household Size	4.074*** (3.213 to 4.936)	3.572*** (1.924 to 5.219)	4.585*** (2.971 to 6.199)	-1.692 (-7.302 to 3.919)	5.740*** (3.020 to 8.459)	6.136*** (4.363 to 7.909)	-0.966 (-3.010 to 1.077)	2.977 (-0.899 to 6.852)
Local Gasoline Price (cons. $)	-1.771*** (-2.286 to -1.257)	-1.815*** (-2.888 to -0.743)	-1.622*** (-2.603 to -0.641)	2.427 (-1.206 to 6.061)	-0.808 (-2.551 to 0.935)	-2.148*** (-3.120 to -1.176)	-2.195*** (-3.831 to -0.559)	-1.658 (-4.252 to 0.935)
Transit Access (census-based)	-0.262*** (-0.329 to -0.195)	-0.181 (-0.451 to 0.0892)	-0.454*** (-0.674 to -0.235)	-0.225** (-0.436 to -0.0137)	-0.564 (-1.387 to 0.260)	-0.350*** (-0.574 to -0.126)	-0.244*** (-0.386 to -0.103)	-0.986*** (-1.673 to -0.299)
Jobs Access 0-5 miles, grav.	-0.430*** (-0.516 to -0.343)	-0.473*** (-0.635 to -0.311)	-1.025*** (-1.332 to -0.719)	-0.0534 (-0.275 to 0.168)	-2.272** (-4.228 to -0.316)	-2.407*** (-2.877 to -1.937)	-0.0858 (-0.275 to 0.103)	-1.242* (-2.631 to 0.147)
Jobs Access 5-50 miles, grav.	0.0591* (-0.00589 to 0.124)	-0.336*** (-0.589 to -0.0827)	0.228*** (0.0743 to 0.382)	-1.154 (-3.151 to 0.843)	1.916*** (1.317 to 2.515)	0.192* (-0.0117 to 0.396)	0.167 (-0.279 to 0.612)	1.612*** (0.816 to 2.407)
Activity mix	-3.078*** (-4.889 to -1.266)	0.0350 (-3.702 to 3.772)	-2.959* (-6.481 to 0.563)	-4.621 (-13.46 to 4.222)	-9.687** (-17.44 to -1.935)	0.0709 (-3.672 to 3.814)	1.523 (-3.386 to 6.431)	4.553 (-4.867 to 13.97)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Perc. Walk/Bike (census-based)	-0.196*** (-0.278 to - 0.114)	0.00159 (-0.143 to 0.146)	-0.0315 (-0.187 to 0.124)	-0.0507 (-0.279 to 0.178)	-0.0503 (-0.391 to 0.291)	-0.496*** (-0.750 to - 0.242)	-0.217** (-0.387 to - 0.0472)	-0.170 (-0.440 to 0.0995)
Road Density	(-0.759 to - 0.577)	-0.198* (-0.419 to 0.0236)	-0.468*** (-0.732 to - 0.204)	0.160 (-0.457 to 0.778)	-1.174*** (-1.802 to - 0.547)	-0.418*** (-0.626 to - 0.211)	-0.109 (-0.408 to 0.191)	-0.502 (-1.148 to 0.144)
Perc. Single Family Homes	0.0207** (0.00313 to 0.0382)	-0.0128 (-0.0487 to 0.0230)	-0.0212 (-0.0604 to 0.0179)	0.263 (-0.181 to 0.708)	0.139*** (0.0532 to 0.224)	0.0562** (0.00558 to 0.107)	-0.0426 (-0.0958 to 0.0106)	0.0993* (-0.0123 to 0.211)
Observations	53,608	10,122	11,734	1,093	5,712	17,846	4,581	2,520
Observations with Zero VMT	7,729	1,230	1,737	517	1,061	1,537	1,187	460
R2: MZ1	0.269	0.234	0.256	0.458	0.229	0.246	0.307	0.235
Decomposition of ME: Effect Conditional on Being Above 0	56%	58%	54%	34%	53%	62%	46%	50%
Effect on Prob of Being Above 0	44%	42%	46%	66%	47%	38%	54%	50%

Robust 95% Confidence Intervals in Parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 22: Tobit Mean Elasticities for Model of Weekday Household VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Number of Vehicles	0.250*** (0.231 to 0.270)	0.144*** (0.0692 to 0.219)	0.138*** (0.0682 to 0.208)	0.835*** (0.415 to 1.255)	0.135*** (0.0514 to 0.219)	0.0635** (0.00138 to 0.126)	0.341** (0.0178 to 0.664)	0.155** (0.0168 to 0.292)
Income ($10,000)	0.132*** (0.121 to 0.143)	0.0636 (-0.0180 to 0.145)	0.171*** (0.0935 to 0.248)	0.253 (-0.283 to 0.789)	0.105** (0.0167 to 0.193)	0.134*** (0.0756 to 0.192)	-0.0219 (-0.170 to 0.126)	0.0858 (-0.0517 to 0.223)
Number of Workers	0.196*** (0.182 to 0.211)	0.241*** (0.205 to 0.277)	0.216*** (0.181 to 0.250)	0.192 (-0.0995 to 0.483)	0.206*** (0.169 to 0.243)	0.201*** (0.176 to 0.226)	0.272*** (0.171 to 0.374)	0.214*** (0.161 to 0.267)
Household Size	0.186*** (0.147 to 0.225)	0.176*** (0.0954 to 0.256)	0.229*** (0.149 to 0.308)	-0.178 (-0.769 to 0.413)	0.245*** (0.133 to 0.358)	0.239*** (0.171 to 0.307)	-0.0665 (-0.207 to 0.0740)	0.145 (-0.0427 to 0.333)
Local Gasoline Price (cons. $)	-0.100*** (-0.129 to -0.0711)	-0.113*** (-0.179 to -0.0462)	-0.102*** (-0.163 to -0.0407)	0.462 (-0.224 to 1.149)	-0.0419 (-0.132 to 0.0484)	-0.0969*** (-0.141 to -0.0532)	-0.203*** (-0.353 to -0.0520)	-0.0978 (-0.250 to 0.0546)
Transit Access (census-based)	-0.0374*** (-0.0472 to -0.0277)	-0.0166 (-0.0415 to 0.00827)	-0.0550*** (-0.0818 to -0.0281)	-0.579** (-1.122 to -0.0351)	-0.0122 (-0.0301 to 0.00577)	-0.0202*** (-0.0333 to -0.00714)	-0.205*** (-0.326 to -0.0850)	-0.0483*** (-0.0825 to -0.0140)
Jobs Access 0-5 miles, grav.	-0.0664*** (-0.0800 to -0.0528)	-0.131*** (-0.177 to -0.0857)	-0.126*** (-0.164 to -0.0872)	-0.145 (-0.748 to 0.458)	-0.0320** (-0.0600 to -0.00406)	-0.119*** (-0.143 to -0.0952)	-0.0471 (-0.151 to 0.0571)	-0.0460* (-0.0993 to 0.00726)
Jobs Access 5-50 miles, grav.	0.0173* (-0.00173 to 0.0363)	-0.194*** (-0.341 to -0.0477)	0.0663*** (0.0217 to 0.111)	-1.054 (-2.866 to 0.758)	0.104*** (0.0730 to 0.135)	0.0344* (-0.00206 to 0.0708)	0.125 (-0.209 to 0.460)	0.132*** (0.0695 to 0.194)
Activity mix	-0.0299*** (-0.0476 to -0.0122)	0.000399 (-0.0422 to 0.0430)	-0.0325 (-0.0713 to 0.00632)	-0.191 (-0.558 to 0.176)	-0.0910** (-0.164 to -0.0177)	0.000509 (-0.0264 to 0.0274)	0.0203 (-0.0452 to 0.0859)	0.0556 (-0.0589 to 0.170)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Perc. Walk/Bike (census-based)	-0.0196*** (-0.0279 to -0.0112)	0.000146 (-0.0132 to 0.0135)	-0.00298 (-0.0178 to 0.0118)	-0.0747 (-0.412 to 0.263)	-0.00463 (-0.0361 to 0.0269)	-0.0200*** (-0.0305 to -0.00955)	-0.0706** (-0.128 to -0.0130)	-0.0220 (-0.0573 to 0.0134)
Road Density	-0.170*** (-0.194 to -0.146)	-0.0741* (-0.157 to 0.00897)	-0.154*** (-0.242 to -0.0656)	0.227 (-0.646 to 1.101)	-0.0640*** (-0.0985 to -0.0296)	-0.0596*** (-0.0894 to -0.0298)	-0.0717 (-0.270 to 0.126)	-0.0875 (-0.202 to 0.0268)
Perc. Single Family Homes	0.0266** (0.00407 to 0.0491)	-0.0182 (-0.0691 to 0.0327)	-0.0237 (-0.0676 to 0.0201)	0.0961 (-0.0633 to 0.256)	0.189*** (0.0727 to 0.305)	0.0795** (0.00806 to 0.151)	-0.0498 (-0.113 to 0.0130)	0.122* (-0.0136 to 0.258)
Observations	53,608	10,122	11,734	1,093	5,712	17,846	4,581	2,520
Observations with Zero VMT	7,729	1,230	1,737	517	1,061	1,537	1,187	460
R2: MZ1	0.269	0.234	0.256	0.458	0.229	0.246	0.307	0.235

Robust 95% Confidence Intervals in Parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 23: Tobit Estimated Coefficients for Model of Weekday Nonwork VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Nonwork Activity More than 2 Hours	12.53*** (11.98 to 13.08)	12.43*** (11.34 to 13.53)	11.46*** (10.30 to 12.63)	11.92*** (7.614 to 16.23)	13.16*** (10.84 to 15.48)	12.98*** (12.10 to 13.86)	11.11*** (9.389 to 12.84)	12.31*** (8.887 to 15.73)
Driver's license	16.90*** (15.72 to 18.09)	15.29*** (12.89 to 17.69)	16.06*** (13.48 to 18.64)	7.942* (-0.804 to 16.69)	14.12*** (9.339 to 18.90)	12.13*** (10.11 to 14.15)	20.40*** (17.23 to 23.56)	13.30*** (7.657 to 18.94)
Male	-0.445** (-0.880 to -0.0103)	-0.332 (-1.244 to 0.580)	-0.197 (-1.178 to 0.783)	-0.968 (-4.733 to 2.796)	-0.283 (-1.841 to 1.275)	-0.109 (-0.798 to 0.580)	-2.064*** (-3.544 to -0.585)	-2.229* (-4.713 to 0.256)
Employed	-4.536*** (-5.239 to -3.833)	-2.668*** (-4.266 to -1.069)	-3.163*** (-4.750 to -1.577)	-6.143 (-14.45 to 2.161)	-6.337*** (-9.050 to -3.624)	-4.366*** (-5.512 to -3.220)	0.799 (-2.027 to 3.625)	-2.010 (-6.272 to 2.252)
Student	-2.392*** (-3.288 to -1.495)	-2.254** (-4.002 to -0.506)	-1.898** (-3.789 to -0.00661)	-6.367* (-12.85 to 0.116)	-3.653* (-7.374 to 0.0674)	-1.163 (-2.818 to 0.492)	-3.134*** (-5.210 to -1.059)	0.118 (-4.560 to 4.797)
Part time Worker	2.606*** (1.799 to 3.414)	2.924*** (1.317 to 4.531)	2.805*** (0.952 to 4.657)	0.372 (-6.011 to 6.755)	2.884 (-0.810 to 6.578)	2.681*** (1.476 to 3.886)	-0.841 (-3.062 to 1.379)	10.20*** (3.492 to 16.90)
Age 25-44	2.777*** (1.697 to 3.857)	1.465 (-0.793 to 3.723)	0.714 (-1.431 to 2.858)	1.078 (-9.882 to 12.04)	0.106 (-4.454 to 4.667)	5.049*** (3.155 to 6.943)	2.468 (-0.505 to 5.440)	8.123*** (3.315 to 12.93)
Age 45-64	2.835*** (1.745 to 3.926)	1.447 (-0.830 to 3.725)	-0.201 (-2.395 to 1.993)	2.375 (-9.068 to 13.82)	1.118 (-3.419 to 5.655)	4.325*** (2.439 to 6.211)	3.007* (-0.126 to 6.141)	8.068*** (3.145 to 12.99)
Age Over 64	3.282*** (1.726 to 4.837)	0.131 (-2.799 to 3.060)	1.324 (-2.421 to 5.070)	1.916 (-17.95 to 21.79)	2.086 (-4.022 to 8.195)	4.407*** (1.911 to 6.903)	2.368 (-2.244 to 6.980)	11.62*** (4.230 to 19.00)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Household Head	0.704*** (0.216 to 1.193)	0.354 (-0.719 to 1.427)	0.625 (-0.514 to 1.764)	-2.558 (-7.524 to 2.409)	0.794 (-0.957 to 2.545)	0.617 (-0.140 to 1.375)	-0.409 (-2.202 to 1.383)	-0.584 (-3.304 to 2.136)
Number of Vehicles	2.020*** (1.686 to 2.353)	0.687 (-0.553 to 1.927)	-0.119 (-1.208 to 0.971)	23.28*** (14.41 to 32.15)	0.181 (-1.377 to 1.739)	0.405 (-0.490 to 1.299)	1.647 (-4.734 to 8.029)	-0.488 (-3.177 to 2.201)
Income ($10,000)	0.811*** (0.655 to 0.967)	0.173 (-0.741 to 1.088)	2.098*** (1.159 to 3.037)	-0.0854 (-3.891 to 3.720)	0.111 (-1.469 to 1.691)	0.738** (0.00695 to 1.470)	1.531** (0.0543 to 3.008)	1.073 (-0.815 to 2.961)
Income Sq. ($10,000)	-0.0233*** (-0.0285 to -0.0181)	-0.0128 (-0.0354 to 0.00979)	-0.0569*** (-0.0813 to -0.0325)	0.00877 (-0.0891 to 0.107)	-0.0120 (-0.0560 to 0.0320)	-0.0232** (-0.0418 to -0.00449)	-0.0476** (-0.0839 to -0.0113)	-0.0215 (-0.0791 to 0.0362)
Household Size	-0.584*** (-0.968 to -0.201)	-0.369 (-1.222 to 0.485)	-1.064*** (-1.801 to -0.328)	-10.50*** (-15.65 to -5.345)	0.637 (-0.889 to 2.164)	0.194 (-0.408 to 0.795)	-2.055*** (-3.359 to -0.752)	0.583 (-1.872 to 3.038)
Local Gasoline Price (cons. $)	-1.031*** (-1.450 to -0.611)	-0.767* (-1.616 to 0.0818)	-1.036** (-1.918 to -0.153)	3.310 (-2.587 to 9.207)	-1.561* (-3.307 to 0.186)	-1.048*** (-1.721 to -0.375)	-0.710 (-2.071 to 0.652)	-0.599 (-3.167 to 1.968)
Transit Access (census-based)	-0.203*** (-0.252 to -0.153)	-0.209** (-0.414 to -0.00435)	-0.153* (-0.309 to 0.00303)	-0.112 (-0.489 to 0.264)	-0.0909 (-0.705 to 0.524)	-0.199*** (-0.319 to -0.0795)	-0.262*** (-0.398 to -0.125)	-0.759** (-1.340 to -0.178)
Jobs Access 0-5 miles, grav.	-0.333*** (-0.403 to -0.264)	-0.287*** (-0.424 to -0.151)	-0.560*** (-0.808 to -0.312)	-0.419* (-0.903 to 0.0658)	-3.327*** (-4.698 to -1.956)	-0.976*** (-1.229 to -0.722)	0.00246 (-0.183 to 0.188)	-1.034*** (-1.650 to -0.418)
Jobs Access 5-50 miles, grav.	-0.0238 (-0.0801 to 0.0326)	-0.0520 (-0.254 to 0.150)	0.0496 (-0.0958 to 0.195)	-4.877*** (-8.057 to -1.697)	0.899*** (0.404 to 1.394)	0.00648 (-0.126 to 0.139)	0.214 (-0.200 to 0.628)	1.088*** (0.308 to 1.867)
Activity mix	-2.873*** (-4.207 to -1.540)	-2.208 (-4.991 to 0.574)	-2.922** (-5.758 to -0.0855)	-9.430 (-23.36 to 4.498)	-6.823** (-13.46 to -0.181)	0.542 (-1.664 to 2.749)	0.829 (-3.415 to 5.073)	-2.597 (-11.30 to 6.107)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Pct Walk/Bike (census)	-0.0495 (-0.116 to 0.0169)	-0.00331 (-0.119 to 0.113)	-0.0139 (-0.182 to 0.154)	0.165 (-0.240 to 0.571)	0.320** (0.0484 to 0.591)	-0.205*** (-0.352 to -0.0582)	-0.240*** (-0.366 to -0.114)	0.0984 (-0.144 to 0.341)
Road Density	-0.530*** (-0.597 to -0.464)	-0.154 (-0.351 to 0.0428)	-0.243** (-0.434 to -0.0522)	0.846 (-0.212 to 1.903)	-2.267*** (-2.852 to -1.682)	-0.402*** (-0.519 to -0.285)	-0.00934 (-0.268 to 0.250)	-0.337 (-0.899 to 0.225)
Pct Single Family Homes	0.00457 (-0.00894 to 0.0181)	0.00305 (-0.0255 to 0.0316)	0.00593 (-0.0247 to 0.0366)	-0.0497 (-0.603 to 0.504)	0.00812 (-0.0723 to 0.0886)	0.0297* (-0.000103 to 0.0594)	-0.0530** (-0.0960 to -0.0100)	0.106* (-0.00466 to 0.218)
Winter	-2.790*** (-3.760 to -1.821)	-2.194** (-4.076 to -0.313)	-3.337*** (-5.483 to -1.191)	-3.290 (-10.71 to 4.126)	-4.403* (-9.075 to 0.269)	-2.735*** (-4.196 to -1.273)	1.978 (-1.219 to 5.174)	-5.982* (-12.95 to 0.989)
Spring	-0.568 (-1.359 to 0.223)	1.282 (-0.410 to 2.975)	-1.601* (-3.309 to 0.107)	0.118 (-5.039 to 5.275)	-1.647 (-5.567 to 2.273)	-1.159* (-2.354 to 0.0363)	-0.404 (-2.573 to 1.766)	-2.693 (-8.487 to 3.101)
Fall	-3.318*** (-4.080 to -2.556)	-3.137*** (-4.686 to -1.589)	-4.444*** (-6.109 to -2.780)	-1.018 (-6.407 to 4.370)	-4.474** (-8.468 to -0.480)	-2.725*** (-3.878 to -1.572)	-2.420** (-4.487 to -0.352)	-7.274** (-13.28 to -1.271)
SACOG	2.663** (0.188 to 5.138)	N/A	19.40** (0.963 to 37.83)	N/A	14.30 (-16.70 to 45.30)	13.66 (-2.653 to 29.97)	N/A	1.939 (-36.16 to 40.04)
SF Bay Area	3.368*** (1.621 to 5.114)	-12.40* (-25.31 to 0.508)	18.35** (0.273 to 36.42)	N/A	9.091 (-20.05 to 38.23)	8.630 (-7.490 to 24.75)	-133.8*** (-212.8 to -54.80)	-1.112 (-43.76 to 41.53)
Central Coast	-1.373 (-3.519 to 0.774)	54.86*** (26.90 to 82.83)	14.30** (0.0365 to 28.57)	N/A	13.72 (-4.941 to 32.38)	10.34* (-0.758 to 21.43)	N/A	18.49* (-2.077 to 39.07)
Central Valley	1.761* (-0.169 to 3.691)	55.60*** (29.27 to 81.94)	15.68** (2.718 to 28.65)	N/A	17.55* (-0.718 to 35.82)	11.30** (0.257 to 22.33)	N/A	18.91* (-2.372 to 40.18)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Mountains	3.797* (-0.291 to 7.886)	N/A	N/A	N/A	3.877 (-1.139 to 8.892)	-9.941*** (-13.95 to -5.929)	N/A	-13.60*** (-20.95 to -6.255)
SCAG	5.209*** (3.139 to 7.278)	-11.16 (-24.90 to 2.575)	20.00** (1.919 to 38.08)	80.36*** (32.39 to 128.3)	11.13 (-17.85 to 40.12)	11.19 (-5.100 to 27.48)	-136.1*** (-215.8 to -56.44)	-2.594 (-44.41 to 39.22)
SANDAG	2.574*** (0.846 to 4.301)	4.063 (-6.052 to 14.18)	18.57** (0.177 to 36.96)	0.689 (-45.09 to 46.46)	26.44* (-4.278 to 57.17)	13.26 (-2.744 to 29.26)	-128.9*** (-204.8 to -53.01)	7.775 (-30.58 to 46.14)
Tuesday	0.102 (-0.658 to 0.862)	-0.563 (-2.040 to 0.914)	-0.303 (-2.038 to 1.432)	-3.228 (-8.223 to 1.766)	1.748 (-1.448 to 4.943)	0.107 (-1.042 to 1.256)	0.493 (-1.710 to 2.697)	1.706 (-2.647 to 6.060)
Wednesday	0.560 (-0.241 to 1.362)	-0.318 (-1.870 to 1.234)	0.186 (-1.644 to 2.016)	1.959 (-4.020 to 7.938)	1.660 (-1.706 to 5.026)	1.023 (-0.225 to 2.272)	-1.161 (-3.402 to 1.079)	0.743 (-4.027 to 5.513)
Thursday	1.048** (0.209 to 1.886)	1.816** (0.0163 to 3.616)	0.599 (-1.174 to 2.372)	5.535 (-1.411 to 12.48)	1.483 (-1.839 to 4.805)	0.813 (-0.499 to 2.125)	0.614 (-1.944 to 3.172)	1.779 (-3.286 to 6.845)
Friday	3.620*** (2.760 to 4.481)	3.275*** (1.567 to 4.983)	3.386*** (1.501 to 5.270)	6.645** (0.406 to 12.88)	4.155** (0.790 to 7.520)	3.904*** (2.508 to 5.300)	1.664 (-0.829 to 4.156)	4.394** (0.0323 to 8.755)
2+Adults <64, no kids	-0.373 (-1.407 to 0.661)	-2.419** (-4.651 to -0.187)	-0.473 (-2.603 to 1.657)	-1.347 (-8.359 to 5.665)	2.170 (-2.350 to 6.691)	-2.679*** (-4.654 to -0.705)	-1.693 (-4.476 to 1.090)	-1.997 (-8.177 to 4.182)
1 adult Child 0-5	3.381* (-0.170 to 6.931)	-0.147 (-6.311 to 6.017)	0.795 (-5.585 to 7.175)	80.84*** (62.90 to 98.78)	-7.306 (-17.26 to 2.653)	1.011 (-4.523 to 6.544)	13.07 (-3.571 to 29.72)	6.188 (-8.005 to 20.38)
2+ adults Child 0-5	1.349 (-0.262 to 2.959)	0.0675 (-3.680 to 3.815)	0.361 (-2.999 to 3.721)	30.02*** (14.84 to 45.19)	0.747 (-5.979 to 7.473)	-4.122*** (-6.949 to -1.295)	2.065 (-3.835 to 7.964)	-2.584 (-11.84 to 6.672)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
1 adult Child 6-17	1.905** (0.0995 to 3.710)	2.136 (-1.790 to 6.061)	1.321 (-2.155 to 4.797)	39.93*** (23.01 to 56.86)	1.547 (-5.976 to 9.070)	-1.076 (-4.553 to 2.401)	2.283 (-4.140 to 8.707)	-3.932 (-11.89 to 4.030)
2+ adults Child 6-17	0.0194 (-1.466 to 1.504)	0.820 (-2.584 to 4.223)	-1.222 (-4.428 to 1.984)	34.93*** (17.26 to 52.60)	0.755 (-5.437 to 6.947)	-3.428*** (-6.035 to -0.820)	2.337 (-3.832 to 8.505)	-4.251 (-13.08 to 4.579)
1 adult >64 No kids	-1.975** (-3.742 to -0.208)	-1.592 (-5.326 to 2.142)	-2.319 (-6.459 to 1.821)	10.31 (-7.120 to 27.74)	-6.294* (-13.17 to 0.583)	-4.614*** (-7.687 to -1.541)	-0.190 (-7.909 to 7.528)	-3.659 (-13.31 to 5.995)
2+ adults >64 No kids	0.928 (-0.843 to 2.699)	0.554 (-3.119 to 4.226)	1.214 (-3.155 to 5.583)	9.807 (-7.483 to 27.10)	-0.712 (-7.610 to 6.186)	-3.172** (-6.143 to -0.202)	4.973 (-3.841 to 13.79)	-3.891 (-13.21 to 5.427)
Selection Variable Urban Low Transit Use	N/A	N/A	-26.08** (-48.21 to -3.960)	8.315 (-97.30 to 113.9)	-25.46 (-72.85 to 21.93)	-22.23** (-40.65 to -3.807)	-43.79** (-84.56 to -3.015)	-73.29** (-133.8 to -12.75)
Selection Variable Suburb MFH	N/A	30.50** (2.895 to 58.11)	N/A	16.48 (-94.35 to 127.3)	30.06** (6.501 to 53.63)	17.48** (2.538 to 32.43)	0.931 (-63.26 to 65.12)	17.79 (-15.68 to 51.25)
Selection Variable Central City	N/A	14.05** (2.427 to 25.67)	29.02*** (16.20 to 41.84)	N/A	-18.20 (-55.34 to 18.95)	21.59*** (10.28 to 32.89)	33.30*** (20.19 to 46.41)	21.24 (-41.84 to 84.33)
Selection Variable Rural	N/A	-40.69 (-96.95 to 15.58)	-58.05*** (-99.43 to -16.68)	-400.1* (-872.5 to 72.19)	N/A	-2.754 (-35.77 to 30.27)	-50.92 (-152.7 to 50.90)	-26.72 (-87.74 to 34.30)
Selection Variable Suburb SFH	N/A	-5.273 (-17.22 to 6.669)	5.314 (-5.118 to 15.75)	-2.284 (-70.31 to 65.74)	5.165 (-18.77 to 29.10)	N/A	5.123 (-24.51 to 34.75)	23.90* (-0.981 to 48.78)
Selection Variable Urban High Transit Use	N/A	-4.965 (-17.97 to 8.043)	7.211 (-4.695 to 19.12)	-72.58*** (-119.4 to -25.76)	20.58 (-5.838 to 47.00)	-2.347 (-14.37 to 9.674)	N/A	32.36* (-0.652 to 65.36)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Selection Variable Rural-In-Urban	N/A	24.29 (-51.11 to 99.70)	47.26** (1.708 to 92.81)	455.4* (-20.04 to 930.8)	-10.65 (-53.06 to 31.75)	-11.00 (-47.77 to 25.77)	54.22 (-70.75 to 179.2)	N/A
Constant	-1.788 (-4.851 to 1.275)	47.54*** (18.48 to 76.59)	-19.07* (-38.76 to 0.614)	19.37 (-40.41 to 79.16)	16.62 (-5.884 to 39.13)	-5.986 (-29.16 to 17.19)	101.7** (9.489 to 194.0)	-30.09 (-95.00 to 34.81)
Sigma	29.45*** (28.77 to 30.13)	26.40*** (25.07 to 27.73)	28.74*** (26.80 to 30.68)	25.72*** (21.40 to 30.04)	37.02*** (35.13 to 38.91)	28.41*** (27.43 to 29.38)	24.22*** (22.32 to 26.11)	34.40*** (30.43 to 38.37)
Observations	66,499	12,146	13,482	1,177	6,545	24,929	5,375	2,845
Observations with Zero VMT	6,823	1,227	1,441	601	375	1,385	1,585	209
R2: MZ1	0.130	0.118	0.113	0.313	0.083	0.093	0.259	0.093

Robust 95% Confidence Intervals in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: Tobit Marginal Effects for Model of Weekday Nonwork VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Number of Vehicles	1.446*** (1.208 to 1.684)	0.492 (-0.395 to 1.379)	-0.0830 (-0.845 to 0.679)	9.574*** (5.944 to 13.20)	0.139 (-1.056 to 1.334)	0.307 (-0.372 to 0.987)	0.951 (-2.730 to 4.631)	-0.350 (-2.275 to 1.576)
Income ($10,000)	0.291*** (0.239 to 0.344)	-0.0448 (-0.412 to 0.322)	0.890*** (0.471 to 1.309)	0.0353 (-0.787 to 0.857)	-0.0334 (-0.825 to 0.759)	0.200 (-0.0726 to 0.473)	0.475* (-0.0819 to 1.032)	0.571 (-0.311 to 1.454)
Household Size	-0.418*** (-0.693 to -0.144)	-0.264 (-0.874 to 0.347)	-0.745*** (-1.259 to -0.230)	-4.317*** (-6.426 to -2.207)	0.489 (-0.682 to 1.660)	0.147 (-0.310 to 0.604)	-1.186*** (-1.933 to -0.440)	0.418 (-1.340 to 2.175)
Local Gasoline Price (cons. $)	-0.738*** (-1.037 to -0.438)	-0.549* (-1.156 to 0.0577)	-0.725** (-1.339 to -0.110)	1.361 (-1.066 to 3.789)	-1.198* (-2.536 to 0.141)	-0.796*** (-1.307 to -0.286)	-0.410 (-1.194 to 0.375)	-0.429 (-2.266 to 1.407)
Transit Access (census-based)	-0.145*** (-0.180 to -0.110)	-0.150** (-0.296 to -0.00341)	-0.107* (-0.216 to 0.00190)	-0.0462 (-0.201 to 0.108)	-0.0698 (-0.541 to 0.402)	-0.151*** (-0.242 to -0.0605)	-0.151*** (-0.229 to -0.0725)	-0.544*** (-0.957 to -0.130)
Jobs Access 0-5 miles, grav.	-0.239*** (-0.288 to -0.189)	-0.205*** (-0.303 to -0.108)	-0.392*** (-0.566 to -0.219)	-0.172* (-0.370 to 0.0255)	-2.553*** (-3.607 to -1.499)	-0.741*** (-0.934 to -0.548)	0.00142 (-0.106 to 0.109)	-0.741*** (-1.182 to -0.300)
Jobs Access 5-50 miles, grav.	-0.0170 (-0.0574 to 0.0233)	-0.0372 (-0.182 to 0.107)	0.0347 (-0.0672 to 0.137)	-2.006*** (-3.318 to -0.694)	0.690*** (0.311 to 1.070)	0.00492 (-0.0955 to 0.105)	0.124 (-0.115 to 0.362)	0.779*** (0.225 to 1.334)
Activity mix	-2.057*** (-3.012 to -1.102)	-1.580 (-3.570 to 0.410)	-2.044** (-4.024 to -0.0642)	-3.879 (-9.563 to 1.806)	-5.236** (-10.34 to -0.132)	0.412 (-1.264 to 2.088)	0.478 (-1.971 to 2.927)	-1.860 (-8.087 to 4.366)
Pct Walk/Bike (census)	-0.0355 (-0.0830 to 0.0121)	-0.00237 (-0.0852 to 0.0805)	-0.00974 (-0.127 to 0.107)	0.0679 (-0.0982 to 0.234)	0.245** (0.0371 to 0.453)	-0.156*** (-0.267 to -0.0443)	-0.139*** (-0.211 to -0.0662)	0.0705 (-0.103 to 0.244)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Road Density	-0.380*** (-0.428 to -0.332)	-0.110 (-0.251 to 0.0307)	-0.170** (-0.304 to -0.0363)	0.348 (-0.0837 to 0.779)	-1.740*** (-2.183 to -1.296)	-0.306*** (-0.394 to -0.217)	-0.00539 (-0.155 to 0.144)	-0.241 (-0.645 to 0.162)
Perc. Single Family Homes	0.00328 (-0.00640 to 0.0130)	0.00218 (-0.0183 to 0.0226)	0.00415 (-0.0173 to 0.0256)	-0.0204 (-0.248 to 0.207)	0.00623 (-0.0555 to 0.0680)	0.0225* (-6.73e-05 to 0.0452)	-0.0306** (-0.0554 to -0.00579)	0.0762* (-0.00259 to 0.155)
Observations	66,499	12,146	13,482	1,177	6,545	24,929	5,375	2,845
Observations with Zero VMT	6,823	1,227	1,441	601	375	1,385	1,585	209
R2: MZ1	0.130	0.118	0.113	0.313	0.083	0.093	0.259	0.093
Decomposition of ME:								
Effect Conditional on Being Above 0	52%	51%	50%	31%	56%	55%	41%	51%
Effect on Prob of Being Above 0	48%	49%	50%	69%	44%	45%	59%	49%

Robust 95% Confidence Intervals in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Tobit Mean Elasticities for Model of Weekday Nonwork VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Number of Vehicles	0.133*** (0.112 to 0.155)	0.0499 (-0.0400 to 0.140)	-0.00776 (-0.0790 to 0.0635)	1.109*** (0.703 to 1.515)	0.00986 (-0.0750 to 0.0947)	0.0296 (-0.0358 to 0.0949)	0.106 (-0.305 to 0.518)	-0.0276 (-0.180 to 0.125)
Income ($10,000)	0.0473*** (0.0350 to 0.0597)	-0.0630 (-0.163 to 0.0369)	0.178*** (0.0834 to 0.273)	0.0664 (-0.598 to 0.731)	-0.0254 (-0.123 to 0.0718)	0.0140 (-0.0502 to 0.0783)	0.124 (-0.0898 to 0.337)	0.103 (-0.0451 to 0.251)
Household Size	-0.0514*** (-0.0852 to -0.0177)	-0.0357 (-0.118 to 0.0470)	-0.100*** (-0.169 to -0.0308)	-1.061*** (-1.519 to -0.603)	0.0416 (-0.0575 to 0.141)	0.0173 (-0.0364 to 0.0711)	-0.242*** (-0.393 to -0.0905)	0.0431 (-0.138 to 0.224)
Local Gasoline Price (cons. $)	-0.0867*** (-0.122 to -0.0516)	-0.0722* (-0.152 to 0.00759)	-0.0924** (-0.170 to -0.0148)	0.468 (-0.374 to 1.310)	-0.0978* (-0.207 to 0.0115)	-0.0857*** (-0.141 to -0.0308)	-0.0849 (-0.247 to 0.0772)	-0.0428 (-0.225 to 0.140)
Transit Access (census-based)	-0.0409*** (-0.0510 to -0.0307)	-0.0261** (-0.0517 to -0.000517)	-0.0260* (-0.0524 to 0.000523)	-0.214 (-0.940 to 0.512)	-0.00255 (-0.0198 to 0.0147)	-0.0216*** (-0.0347 to -0.00851)	-0.286*** (-0.436 to -0.136)	-0.0408*** (-0.0716 to -0.0100)
Jobs Access 0-5 miles, grav.	-0.0685*** (-0.0830 to -0.0540)	-0.105*** (-0.156 to -0.0548)	-0.0914*** (-0.132 to -0.0505)	-0.830* (-1.750 to 0.0912)	-0.0588*** (-0.0838 to -0.0338)	-0.0852*** (-0.108 to -0.0628)	0.00168 (-0.125 to 0.128)	-0.0437*** (-0.0702 to -0.0173)
Jobs Access 5-50 miles, grav.	-0.00995 (-0.0336 to 0.0137)	-0.0414 (-0.202 to 0.119)	0.0203 (-0.0394 to 0.0799)	-3.249*** (-5.318 to -1.180)	0.0615*** (0.0285 to 0.0946)	0.00210 (-0.0408 to 0.0450)	0.198 (-0.184 to 0.580)	0.103*** (0.0327 to 0.173)
Activity mix	-0.0388*** (-0.0569 to -0.0207)	-0.0349 (-0.0789 to 0.00915)	-0.0421** (-0.0828 to -0.00140)	-0.274 (-0.667 to 0.119)	-0.0737** (-0.146 to -0.00118)	0.00672 (-0.0206 to 0.0340)	0.0139 (-0.0570 to 0.0848)	-0.0373 (-0.162 to 0.0879)
Perc. Walk/Bike (census)	-0.00631 (-0.0148 to 0.00219)	-0.000390 (-0.0141 to 0.0133)	-0.00162 (-0.0211 to 0.0179)	0.176 (-0.245 to 0.597)	0.0325** (0.00549 to 0.0595)	-0.0135*** (-0.0233 to -0.00376)	-0.0953*** (-0.146 to -0.0443)	0.0142 (-0.0203 to 0.0486)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Road Density	-0.190*** (-0.214 to -0.166)	-0.0821 (-0.187 to 0.0231)	-0.108** (-0.194 to -0.0224)	0.893* (-0.157 to 1.942)	-0.143*** (-0.179 to -0.106)	-0.100*** (-0.130 to -0.0707)	-0.00782 (-0.225 to 0.209)	-0.0666 (-0.179 to 0.0459)
Perc. Single Family Homes	0.00891 (-0.0174 to 0.0352)	0.00659 (-0.0552 to 0.0683)	0.00934 (-0.0390 to 0.0577)	-0.0153 (-0.186 to 0.155)	0.0129 (-0.115 to 0.140)	0.0738* (-5.00e-05 to 0.148)	-0.0848** (-0.154 to -0.0155)	0.153* (-0.00138 to 0.307)
Observations	66,499	12,146	13,482	1,177	6,545	24,929	5,375	2,845
Observations with Zero VMT	6,823	1,227	1,441	601	375	1,385	1,585	209
R2: MZ1	0.130	0.118	0.113	0.313	0.083	0.093	0.259	0.093

Robust 95% Confidence Intervals in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: Tobit Estimated Coefficients for Model of Home-To-Work Commute VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Household Head	0.533*** (0.163 to 0.903)	0.125 (-0.423 to 0.672)	0.0887 (-0.564 to 0.741)	2.509 (-0.591 to 5.608)	1.352** (0.297 to 2.407)	0.232 (-0.442 to 0.905)	1.060* (-0.0679 to 2.188)	0.320 (-1.644 to 2.284)
Male	2.433*** (2.137 to 2.728)	1.341*** (0.862 to 1.820)	2.184*** (1.624 to 2.745)	0.819 (-1.407 to 3.045)	2.566*** (1.583 to 3.549)	3.078*** (2.551 to 3.605)	0.974* (-0.00112 to 1.948)	3.107*** (1.367 to 4.847)
Part time Worker	-3.341*** (-3.834 to -2.848)	-2.468*** (-3.214 to -1.721)	-2.767*** (-3.622 to -1.912)	2.053 (-2.473 to 6.579)	-2.400** (-4.613 to -0.187)	-3.717*** (-4.503 to -2.930)	-2.058** (-3.816 to -0.300)	-0.572 (-4.594 to 3.451)
Age 25-44	2.675*** (2.120 to 3.230)	1.974*** (1.108 to 2.839)	2.000*** (1.064 to 2.935)	-0.565 (-6.199 to 5.070)	1.719* (-0.106 to 3.544)	3.181*** (2.106 to 4.257)	1.789* (-0.0789 to 3.657)	0.852 (-2.010 to 3.714)
Age 45-64	1.664*** (1.084 to 2.243)	1.395*** (0.528 to 2.261)	1.024** (0.0638 to 1.984)	0.223 (-5.561 to 6.007)	0.786 (-1.040 to 2.613)	1.801*** (0.605 to 2.997)	1.917** (0.00722 to 3.827)	-0.223 (-3.043 to 2.598)
Age Over 64	0.404 (-0.917 to 1.725)	-0.179 (-2.263 to 1.904)	-2.017 (-4.549 to 0.514)	7.361 (-10.14 to 24.86)	0.453 (-5.110 to 6.015)	0.935 (-1.246 to 3.115)	-0.103 (-4.542 to 4.336)	7.021 (-3.552 to 17.59)
Driver's license	6.952*** (5.833 to 8.072)	3.866*** (2.248 to 5.484)	4.305*** (2.664 to 5.945)	7.227* (-0.0801 to 14.53)	6.368*** (3.256 to 9.480)	6.818*** (4.473 to 9.163)	5.870*** (3.280 to 8.461)	9.610*** (5.975 to 13.24)
Number of Vehicles	0.873*** (0.612 to 1.133)	0.0285 (-0.577 to 0.634)	-0.354 (-0.892 to 0.185)	4.156 (-0.987 to 9.299)	0.131 (-0.676 to 0.937)	-0.0925 (-0.744 to 0.559)	-0.596 (-3.402 to 2.211)	0.0102 (-1.341 to 1.362)
Income ($10,000)	0.507*** (0.402 to 0.612)	0.144 (-0.308 to 0.596)	0.629*** (0.224 to 1.033)	0.399 (-1.195 to 1.993)	0.336 (-0.287 to 0.959)	0.669*** (0.231 to 1.108)	0.125 (-0.731 to 0.981)	0.585 (-0.351 to 1.521)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Income Sq. ($10,000)	-0.0144*** (-0.0180 to -0.0109)	-0.00199 (-0.0124 to 0.00840)	-0.0187*** (-0.0289 to -0.00855)	-0.00898 (-0.0462 to 0.0282)	-0.0163* (-0.0343 to 0.00164)	-0.0187*** (-0.0299 to -0.00749)	-0.00563 (-0.0254 to 0.0142)	-0.0221 (-0.0534 to 0.00924)
Household Size	-0.357*** (-0.576 to -0.138)	-0.300* (-0.647 to 0.0477)	-0.288 (-0.666 to 0.0894)	-2.098 (-5.000 to 0.805)	-0.360 (-0.998 to 0.278)	-0.163 (-0.590 to 0.264)	-0.541 (-1.259 to 0.177)	0.463 (-0.722 to 1.648)
Local Gasoline Price (cons. $)	-0.452*** (-0.765 to -0.139)	-0.308 (-0.884 to 0.268)	-0.731*** (-1.176 to -0.286)	-0.849 (-3.967 to 2.269)	-0.541 (-1.512 to 0.430)	-0.0183 (-0.693 to 0.657)	-1.290*** (-2.099 to -0.481)	-1.791** (-3.576 to -0.00640)
Transit Access (census-based)	0.0500*** (0.0128 to 0.0873)	0.0472 (-0.0653 to 0.160)	-0.0721 (-0.177 to 0.0330)	-0.101 (-0.305 to 0.103)	-0.931*** (-1.281 to -0.582)	-0.184*** (-0.295 to -0.0718)	0.0622* (-0.00583 to 0.130)	-0.713*** (-1.187 to -0.240)
Jobs Access 0-5 miles, grav.	-0.314*** (-0.362 to -0.267)	-0.261*** (-0.325 to -0.197)	-0.498*** (-0.616 to -0.381)	0.0326 (-0.162 to 0.227)	-1.301*** (-2.041 to -0.561)	-1.211*** (-1.435 to -0.987)	-0.0218 (-0.130 to 0.0869)	-1.394*** (-2.092 to -0.696)
Jobs Access 5-50 miles, grav.	-0.0406** (-0.0741 to -0.00707)	0.00574 (-0.0793 to 0.0908)	0.0444 (-0.0177 to 0.106)	-1.123 (-2.621 to 0.375)	0.526*** (0.277 to 0.776)	0.00988 (-0.133 to 0.152)	0.0967 (-0.134 to 0.328)	0.659*** (0.199 to 1.119)
Activity mix	-1.609*** (-2.425 to -0.792)	0.136 (-1.150 to 1.423)	-1.144 (-2.579 to 0.291)	-2.136 (-9.429 to 5.158)	-9.534*** (-12.93 to -6.139)	0.909 (-0.699 to 2.518)	-4.838*** (-7.627 to -2.048)	3.539 (-1.532 to 8.611)
Pct Walk/Bike (census)	-0.101*** (-0.144 to -0.0571)	-0.0595 (-0.133 to 0.0139)	-0.136*** (-0.210 to -0.0628)	-0.0321 (-0.229 to 0.165)	0.0686 (-0.0689 to 0.206)	-0.158** (-0.282 to -0.0347)	-0.127*** (-0.224 to -0.0305)	-0.0165 (-0.152 to 0.119)
Road Density	-0.233*** (-0.274 to -0.193)	0.0284 (-0.0578 to 0.115)	-0.132** (-0.234 to -0.0301)	0.0274 (-0.550 to 0.605)	-0.452*** (-0.753 to -0.150)	-0.113** (-0.208 to -0.0186)	0.103 (-0.0513 to 0.258)	-0.230 (-0.557 to 0.0980)
Perc. Single Family Homes	0.0215*** (0.0135 to 0.0295)	0.00329 (-0.00926 to 0.0158)	0.0171** (0.000717 to 0.0334)	0.00609 (-0.335 to 0.347)	0.0857*** (0.0491 to 0.122)	0.0333*** (0.0113 to 0.0553)	-0.0257* (-0.0537 to 0.00229)	0.0304 (-0.0331 to 0.0939)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Pct Transit Use Work (census)	0.0777*** (0.0474 to 0.108)	0.166*** (0.122 to 0.211)	0.194*** (0.124 to 0.263)	-0.546*** (-0.658 to -0.433)	0.923*** (0.660 to 1.185)	0.303*** (0.245 to 0.360)	-0.402*** (-0.465 to -0.340)	0.691*** (0.317 to 1.065)
Activity mix Work	5.245*** (4.323 to 6.167)	-0.510 (-1.887 to 0.867)	2.845*** (1.392 to 4.299)	7.345*** (2.307 to 12.38)	6.663*** (3.491 to 9.835)	6.347*** (4.554 to 8.140)	7.306*** (5.314 to 9.298)	2.166 (-2.201 to 6.534)
Pct Walk/Bike Work (census)	-0.0295*** (-0.0476 to -0.0114)	0.0570*** (0.0268 to 0.0872)	0.0747*** (0.0397 to 0.110)	-0.290*** (-0.364 to -0.216)	-0.188*** (-0.283 to -0.0931)	0.00486 (-0.0284 to 0.0381)	-0.122*** (-0.152 to -0.0919)	-0.164*** (-0.279 to -0.0491)
Road Density Work	-0.0427** (-0.0798 to -0.00559)	-0.378*** (-0.442 to -0.313)	-0.255*** (-0.323 to -0.186)	-0.147 (-0.452 to 0.158)	0.476*** (0.332 to 0.621)	0.0205 (-0.0447 to 0.0858)	-0.257*** (-0.374 to -0.141)	0.132 (-0.0926 to 0.356)
Winter	-0.965*** (-1.576 to -0.354)	-0.578 (-1.634 to 0.478)	-0.653 (-1.854 to 0.548)	-3.358* (-7.068 to 0.352)	-2.236* (-4.609 to 0.137)	-0.205 (-1.241 to 0.832)	-2.089* (-4.184 to 0.00651)	-6.328** (-11.23 to -1.429)
Spring	-0.533** (-1.034 to -0.0315)	-0.146 (-1.077 to 0.786)	-0.625 (-1.604 to 0.353)	-3.339** (-6.195 to -0.482)	-0.775 (-2.838 to 1.288)	-0.546 (-1.360 to 0.269)	-1.241* (-2.681 to 0.200)	-3.170 (-7.538 to 1.197)
Fall	-0.197 (-0.764 to 0.369)	-0.182 (-0.979 to 0.615)	-0.488 (-1.436 to 0.460)	1.823 (-1.288 to 4.934)	-2.142** (-4.197 to -0.0865)	0.512 (-0.562 to 1.587)	-1.699** (-3.055 to -0.343)	-3.879 (-8.530 to 0.772)
SACOG	3.369*** (1.955 to 4.782)	N/A	5.931 (-1.957 to 13.82)	N/A	-2.752 (-14.61 to 9.102)	8.479* (-1.050 to 18.01)	N/A	-2.615 (-22.82 to 17.59)
SF Bay Area	5.120*** (4.281 to 5.960)	2.837 (-3.559 to 9.233)	8.804** (1.079 to 16.53)	N/A	-6.990 (-19.11 to 5.129)	8.913* (-0.538 to 18.36)	-10.63 (-24.00 to 2.742)	-9.966 (-33.09 to 13.16)
Central Coast	3.749*** (2.568 to 4.931)	9.578 (-8.383 to 27.54)	7.289** (0.749 to 13.83)	N/A	0.721 (-6.394 to 7.836)	10.99*** (4.108 to 17.87)	0.876 (-20.79 to 22.54)	3.898 (-7.689 to 15.48)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Central Valley	4.407*** (3.468 to 5.345)	17.25* (-0.965 to 35.47)	8.746*** (2.506 to 14.99)	N/A	-0.480 (-7.313 to 6.353)	10.97*** (4.290 to 17.65)	N/A	4.427 (-7.463 to 16.32)
Mountains	4.027*** (1.863 to 6.191)	N/A	N/A	N/A	4.816*** (2.434 to 7.199)	-3.809 (-10.40 to 2.782)	N/A	-3.973* (-8.251 to 0.306)
SCAG	8.074*** (7.055 to 9.093)	5.512 (-1.260 to 12.29)	9.799** (2.140 to 17.46)	-51.68 (-51.68 to -51.68)	-1.784 (-13.71 to 10.14)	12.90*** (3.576 to 22.23)	-15.83** (-30.55 to -1.123)	-5.924 (-28.79 to 16.94)
SANDAG	5.055*** (4.166 to 5.945)	4.678** (0.123 to 9.234)	10.28*** (2.512 to 18.04)	-18.68* (-38.66 to 1.297)	-0.452 (-11.89 to 10.98)	9.529** (0.115 to 18.94)	-3.224 (-7.743 to 1.296)	-4.873 (-25.37 to 15.63)
Tuesday	-0.336 (-0.828 to 0.157)	0.235 (-0.388 to 0.858)	-0.291 (-1.018 to 0.436)	-1.107 (-3.523 to 1.310)	0.0373 (-1.507 to 1.582)	-0.966* (-1.985 to 0.0528)	0.262 (-0.835 to 1.360)	2.262* (-0.0758 to 4.599)
Wednesday	-0.356 (-0.900 to 0.189)	0.549 (-0.177 to 1.275)	-0.333 (-1.155 to 0.489)	-1.752 (-4.685 to 1.181)	-1.598** (-3.193 to -0.00256)	-0.805 (-1.929 to 0.320)	0.414 (-0.885 to 1.714)	1.846 (-0.827 to 4.519)
Thursday	-0.301 (-0.858 to 0.257)	0.112 (-0.715 to 0.940)	-0.276 (-1.128 to 0.576)	-0.383 (-3.448 to 2.683)	-0.821 (-2.513 to 0.871)	-0.465 (-1.595 to 0.664)	-0.0474 (-1.363 to 1.268)	2.186* (-0.176 to 4.547)
Friday	-0.642** (-1.175 to -0.109)	0.0978 (-0.588 to 0.784)	-0.551 (-1.374 to 0.273)	1.601 (-1.469 to 4.670)	-1.605** (-3.196 to -0.0132)	-1.135* (-2.291 to 0.0211)	0.293 (-1.068 to 1.655)	2.642** (0.198 to 5.085)
Saturday	-1.421*** (-2.364 to -0.478)	-1.345** (-2.471 to -0.219)	-0.436 (-2.149 to 1.277)	-2.781 (-9.960 to 4.398)	0.0304 (-4.180 to 4.240)	-1.940** (-3.730 to -0.150)	0.298 (-2.266 to 2.863)	2.177 (-4.624 to 8.978)
Sunday	0.610 (-0.574 to 1.794)	-0.589 (-1.809 to 0.632)	0.177 (-1.758 to 2.112)	-13.31*** (-22.70 to -3.916)	3.140 (-1.220 to 7.501)	0.895 (-1.605 to 3.394)	0.447 (-2.012 to 2.907)	2.641 (-3.957 to 9.240)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
2+Adults <64, no kids	-0.371 (-1.031 to 0.288)	-0.948** (-1.836 to -0.0598)	-0.879 (-1.980 to 0.223)	-0.446 (-4.554 to 3.662)	-1.151 (-3.452 to 1.151)	-1.071 (-2.485 to 0.342)	-0.430 (-2.263 to 1.403)	0.837 (-2.090 to 3.765)
1 adult Child 0-5	-0.468 (-2.694 to 1.758)	0.635 (-3.222 to 4.493)	-0.733 (-4.564 to 3.098)	11.89*** (3.281 to 20.49)	-2.026 (-11.32 to 7.272)	-2.039 (-5.855 to 1.778)	-2.323 (-6.578 to 1.933)	-1.773 (-7.628 to 4.083)
2+ adults Child 0-5	1.021** (0.135 to 1.907)	0.0965 (-1.392 to 1.585)	0.539 (-1.186 to 2.265)	7.779* (-1.079 to 16.64)	-1.299 (-4.572 to 1.975)	0.518 (-1.199 to 2.234)	1.036 (-1.952 to 4.024)	-2.074 (-7.059 to 2.912)
1 adult Child 6-17	-0.488 (-1.704 to 0.728)	-1.225 (-3.438 to 0.988)	-0.901 (-3.211 to 1.409)	N/A	-1.236 (-5.776 to 3.304)	-0.112 (-2.385 to 2.161)	-3.580** (-6.888 to -0.271)	-2.498 (-7.403 to 2.408)
2+ adults Child 6-17	-0.431 (-1.366 to 0.503)	-0.559 (-1.966 to 0.847)	-0.843 (-2.409 to 0.722)	-2.159 (-12.21 to 7.895)	-1.878 (-4.902 to 1.146)	-0.730 (-2.490 to 1.030)	1.653 (-1.191 to 4.496)	0.342 (-4.073 to 4.757)
1 adult >64 No kids	-0.366 (-2.149 to 1.417)	-0.272 (-3.290 to 2.745)	2.473 (-0.803 to 5.750)	-11.84 (-28.55 to 4.863)	-2.445 (-12.41 to 7.517)	-0.174 (-3.520 to 3.171)	2.338 (-3.239 to 7.914)	-10.65 (-23.80 to 2.490)
2+ adults >64 No kids	-1.572* (-3.427 to 0.283)	0.356 (-3.039 to 3.751)	1.345 (-2.698 to 5.389)	-3.817 (-20.52 to 12.89)	-6.398* (-13.56 to 0.764)	-1.844 (-4.903 to 1.215)	2.241 (-3.251 to 7.734)	-16.97** (-29.90 to -4.028)
Selection Variable Urban Low Transit Use	N/A	N/A	-11.67** (-22.53 to -0.808)	-16.91 (-69.38 to 35.56)	-9.304 (-34.06 to 15.46)	-18.02*** (-28.82 to -7.207)	-50.73*** (-75.42 to -26.03)	-36.66** (-69.96 to -3.368)
Selection Variable Suburb MFH	N/A	-13.86 (-30.57 to 2.854)	N/A	-19.13 (-76.37 to 38.10)	-0.843 (-11.38 to 9.694)	-5.919 (-15.39 to 3.548)	5.045 (-30.95 to 41.04)	6.694 (-9.180 to 22.57)
Selection Variable Central City	N/A	2.976 (-2.978 to 8.930)	10.45*** (4.225 to 16.68)	N/A	6.898 (-15.87 to 29.67)	7.430* (-0.973 to 15.83)	12.53*** (4.151 to 20.90)	28.87** (3.118 to 54.63)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Selection Variable Rural	N/A	-16.11 (-46.79 to 14.56)	-30.56*** (-50.01 to -11.11)	-59.32 (-196.9 to 78.29)	N/A	-29.67*** (-50.98 to -8.357)	-91.76*** (-149.9 to -33.61)	8.278 (-27.90 to 44.45)
Selection Variable Suburb SFH	N/A	-4.307 (-10.28 to 1.669)	-1.385 (-5.575 to 2.805)	0.330 (-20.23 to 20.89)	-6.432 (-14.68 to 1.816)	N/A	-1.389 (-13.84 to 11.06)	-5.552 (-16.48 to 5.374)
Selection Variable Urban High Transit Use	N/A	3.495 (-5.879 to 12.87)	2.595 (-3.478 to 8.668)	1.084 (-22.73 to 24.89)	6.120 (-12.98 to 25.22)	9.425** (0.924 to 17.93)	N/A	1.393 (-17.97 to 20.75)
Selection Variable Rural-In-Urban	N/A	30.96 (-10.83 to 72.76)	32.30*** (8.453 to 56.15)	95.35 (-61.61 to 252.3)	3.402 (-21.88 to 28.68)	35.81*** (11.06 to 60.55)	127.0*** (50.55 to 203.5)	N/A
Constant	-4.342*** (-7.199 to -1.485)	4.139 (-11.11 to 19.39)	-2.969 (-12.49 to 6.550)	18.14 (-17.55 to 53.83)	-1.638 (-15.52 to 12.24)	-21.54*** (-37.30 to -5.794)	2.786 (-23.96 to 29.53)	6.259 (-29.88 to 42.40)
Sigma	15.45*** (12.49 to 18.41)	10.35*** (9.096 to 11.60)	12.25*** (11.78 to 12.73)	10.66*** (9.390 to 11.92)	15.05*** (14.33 to 15.77)	18.36*** (12.04 to 24.68)	11.32*** (10.64 to 12.00)	15.83*** (14.59 to 17.07)
Observations	44,987	8,620	9,537	768	4,069	16,925	3,391	1,677
Observations with Zero VMT (telecommuters)	3,309	566	600	336	223	768	693	123
R2: MZ1	0.090	0.092	0.101	0.656	0.192	0.079	0.348	0.167

Robust 95% Confidence Intervals in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27: Tobit Marginal Effects for Model of Home-To-Work Commute VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Number of Vehicles	0.671*** (0.493 to 0.848)	0.0234 (-0.474 to 0.521)	-0.285 (-0.718 to 0.148)	2.131 (-0.491 to 4.752)	0.104 (-0.535 to 0.742)	-0.0714 (-0.578 to 0.435)	-0.421 (-2.406 to 1.563)	0.00762 (-1.005 to 1.020)
Income ($10,000)	0.179*** (0.149 to 0.208)	0.0851 (-0.124 to 0.295)	0.261** (0.0589 to 0.463)	0.101 (-0.324 to 0.527)	0.0773 (-0.225 to 0.379)	0.203*** (0.0521 to 0.355)	0.0247 (-0.369 to 0.419)	0.210 (-0.213 to 0.633)
Household Size	-0.274*** (-0.449 to -0.0998)	-0.246* (-0.534 to 0.0417)	-0.232 (-0.536 to 0.0719)	-1.075 (-2.555 to 0.404)	-0.286 (-0.791 to 0.219)	-0.126 (-0.462 to 0.210)	-0.383 (-0.890 to 0.124)	0.347 (-0.540 to 1.234)
Local Gasoline Price (cons. $)	-0.347*** (-0.599 to -0.0959)	-0.253 (-0.732 to 0.225)	-0.589*** (-0.946 to -0.231)	-0.435 (-2.032 to 1.161)	-0.429 (-1.197 to 0.339)	-0.0141 (-0.536 to 0.508)	-0.912*** (-1.484 to -0.341)	-1.343** (-2.676 to -0.00969)
Transit Access (census-based)	0.0384*** (0.00980 to 0.0671)	0.0388 (-0.0540 to 0.132)	-0.0580 (-0.143 to 0.0266)	-0.0517 (-0.156 to 0.0527)	-0.738*** (-1.014 to -0.462)	-0.142*** (-0.225 to -0.0587)	0.0440* (-0.00406 to 0.0920)	-0.535*** (-0.887 to -0.182)
Jobs Access 0-5 miles, grav.	-0.242*** (-0.275 to -0.209)	-0.214*** (-0.266 to -0.163)	-0.401*** (-0.497 to -0.306)	0.0167 (-0.0828 to 0.116)	-1.031*** (-1.618 to -0.444)	-0.936*** (-1.073 to -0.798)	-0.0154 (-0.0923 to 0.0614)	-1.045*** (-1.568 to -0.522)
Jobs Access 5-50 miles, grav.	-0.0312** (-0.0577 to -0.00472)	0.00472 (-0.0651 to 0.0746)	0.0357 (-0.0143 to 0.0858)	-0.576 (-1.346 to 0.194)	0.417*** (0.220 to 0.615)	0.00763 (-0.102 to 0.117)	0.0684 (-0.0949 to 0.232)	0.494*** (0.150 to 0.838)
Activity mix	-1.236*** (-1.865 to -0.607)	0.112 (-0.944 to 1.169)	-0.921 (-2.076 to 0.234)	-1.095 (-4.826 to 2.636)	-7.556*** (-10.24 to -4.869)	0.703 (-0.536 to 1.941)	-3.423*** (-5.389 to -1.456)	2.653 (-1.147 to 6.453)
Perc. Walk/Bike (census)	-0.0773*** (-0.110 to -0.0443)	-0.0489 (-0.110 to 0.0121)	-0.110*** (-0.169 to -0.0507)	-0.0164 (-0.117 to 0.0845)	0.0544 (-0.0545 to 0.163)	-0.122** (-0.219 to -0.0254)	-0.0902*** (-0.159 to -0.0218)	-0.0124 (-0.114 to 0.0890)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Road Density	-0.179*** (-0.215 to -0.144)	0.0233 (-0.0474 to 0.0940)	-0.106** (-0.188 to -0.0242)	0.0141 (-0.282 to 0.310)	-0.358*** (-0.597 to -0.119)	-0.0874** (-0.166 to -0.00917)	0.0731 (-0.0363 to 0.182)	-0.172 (-0.418 to 0.0733)
Perc. Single Family Homes	0.0165*** (0.0106 to 0.0224)	0.00270 (-0.00762 to 0.0130)	0.0137** (0.000601 to 0.0269)	0.00312 (-0.171 to 0.178)	0.0679*** (0.0390 to 0.0969)	0.0257*** (0.00950 to 0.0419)	-0.0182* (-0.0380 to 0.00162)	0.0228 (-0.0248 to 0.0703)
Pct Transit Use Work (census)	0.0597*** (0.0356 to 0.0839)	0.137*** (0.0995 to 0.174)	0.156*** (0.100 to 0.212)	-0.280*** (-0.335 to -0.224)	0.731*** (0.523 to 0.939)	0.234*** (0.183 to 0.285)	-0.285*** (-0.328 to -0.242)	0.518*** (0.238 to 0.797)
Activity mix Work	4.031*** (3.439 to 4.622)	-0.419 (-1.542 to 0.704)	2.291*** (1.121 to 3.461)	3.766*** (1.202 to 6.329)	5.281*** (2.775 to 7.787)	4.904*** (3.830 to 5.978)	5.169*** (3.777 to 6.561)	1.624 (-1.646 to 4.894)
Pct Walk/Bike Work (census)	-0.0227*** (-0.0362 to -0.00917)	0.0469*** (0.0221 to 0.0717)	0.0602*** (0.0320 to 0.0883)	-0.149*** (-0.186 to -0.112)	-0.149*** (-0.224 to -0.0740)	0.00376 (-0.0221 to 0.0296)	-0.0864*** (-0.108 to -0.0652)	-0.123*** (-0.209 to -0.0370)
Road Density Work	-0.0328** (-0.0610 to -0.00466)	-0.310*** (-0.363 to -0.258)	-0.205*** (-0.260 to -0.150)	-0.0753 (-0.232 to 0.0811)	0.378*** (0.263 to 0.492)	0.0159 (-0.0349 to 0.0667)	-0.182*** (-0.265 to -0.0995)	0.0989 (-0.0691 to 0.267)
Observations	44,987	8,620	9,537	768	4,069	16,925	3,391	1,677
Observations with Zero VMT	3,309	566	600	336	223	768	693	123
R2: MZ1	0.090	0.092	0.101	0.656	0.192	0.079	0.348	0.167

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Decomposition of ME:								
Effect Conditional on Being Above 0	56%	62%	60%	39%	60%	56%	53%	55%
Effect on Prob of Being Above 0	44%	38%	40%	61%	40%	44%	47%	45%

Robust 95% Confidence Intervals in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 28: Tobit Mean Elasticities for Model of Home-To-Work Commute VMT

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Number of Vehicles	0.111*** (0.0846 to 0.137)	0.00480 (-0.0970 to 0.107)	-0.0512 (-0.129 to 0.0266)	0.524 (-0.112 to 1.161)	0.0179 (-0.0923 to 0.128)	-0.0108 (-0.0882 to 0.0666)	-0.0808 (-0.462 to 0.300)	0.00129 (-0.171 to 0.173)
Income ($10,000)	0.0580*** (0.0436 to 0.0725)	0.0659 (-0.0732 to 0.205)	0.0929* (-0.00461 to 0.190)	0.173 (-0.615 to 0.960)	-0.0145 (-0.119 to 0.0902)	0.0580* (-0.00497 to 0.121)	-0.00637 (-0.266 to 0.253)	0.0459 (-0.109 to 0.201)
Household Size	-0.0565*** (-0.0943 to -0.0187)	-0.0628* (-0.137 to 0.0116)	-0.0544 (-0.126 to 0.0170)	-0.515 (-1.231 to 0.200)	-0.0574 (-0.159 to 0.0442)	-0.0225 (-0.0842 to 0.0391)	-0.115 (-0.269 to 0.0381)	0.0731 (-0.113 to 0.259)
Local Gasoline Price (cons. $)	-0.0642** (-0.113 to -0.0150)	-0.0587 (-0.171 to 0.0540)	-0.123*** (-0.198 to -0.0481)	-0.268 (-1.251 to 0.715)	-0.0754 (-0.210 to 0.0594)	-0.00219 (-0.0831 to 0.0787)	-0.270*** (-0.440 to -0.101)	-0.257** (-0.509 to -0.00388)
Transit Access (census-based)	0.0166*** (0.00421 to 0.0289)	0.0121 (-0.0169 to 0.0411)	-0.0238 (-0.0587 to 0.0112)	-0.435 (-1.323 to 0.452)	-0.0617*** (-0.0864 to -0.0371)	-0.0299*** (-0.0475 to -0.0123)	0.117* (-0.0107 to 0.244)	-0.0830*** (-0.141 to -0.0249)
Jobs Access 0-5 miles, grav.	-0.112*** (-0.130 to -0.0948)	-0.203*** (-0.253 to -0.153)	-0.168*** (-0.208 to -0.127)	0.150 (-0.741 to 1.042)	-0.0541*** (-0.0857 to -0.0224)	-0.162*** (-0.193 to -0.131)	-0.0259 (-0.155 to 0.103)	-0.117*** (-0.179 to -0.0541)
Jobs Access 5-50 miles, grav.	-0.0295** (-0.0555 to -0.00351)	0.00937 (-0.129 to 0.148)	0.0361 (-0.0145 to 0.0868)	-1.712 (-4.025 to 0.602)	0.0827*** (0.0447 to 0.121)	0.00483 (-0.0639 to 0.0735)	0.153 (-0.212 to 0.519)	0.125*** (0.0393 to 0.210)
Activity mix	-0.0384*** (-0.0585 to -0.0184)	0.00460 (-0.0386 to 0.0478)	-0.0329 (-0.0743 to 0.00856)	-0.140 (-0.616 to 0.337)	-0.245*** (-0.333 to -0.156)	0.0171 (-0.0129 to 0.0472)	-0.144*** (-0.229 to -0.0600)	0.104 (-0.0437 to 0.252)
Pct Walk/Bike (census)	-0.0227*** (-0.0327 to -0.0127)	-0.0148 (-0.0339 to 0.00422)	-0.0313*** (-0.0486 to -0.0140)	-0.0825 (-0.591 to 0.426)	0.0187 (-0.0186 to 0.0560)	-0.0161** (-0.0296 to -0.00265)	-0.0903** (-0.162 to -0.0186)	-0.00540 (-0.0498 to 0.0390)

INDEPENDENT VARIABLES	All (No RSS Controls)	Urban Low Transit Use	Suburb MFH	Central City	Rural	Suburb SFH	Urban High Transit Use	Rural In Urban
Road Density	-0.147*** (-0.183 to -0.112)	0.0321 (-0.0649 to 0.129)	-0.117** (-0.207 to -0.0261)	0.0656 (-1.315 to 1.446)	-0.0650*** (-0.109 to -0.0208)	-0.0432** (-0.0859 to -0.000476)	0.152 (-0.0750 to 0.379)	-0.0926 (-0.226 to 0.0405)
Perc. Single Family Homes	0.0731*** (0.0480 to 0.0983)	0.0151 (-0.0426 to 0.0728)	0.0513** (0.00275 to 0.0998)	0.00412 (-0.226 to 0.234)	0.315*** (0.183 to 0.448)	0.125*** (0.0492 to 0.201)	-0.0715* (-0.150 to 0.00702)	0.0913 (-0.0988 to 0.281)
Pct Transit Use Work (census)	0.0285*** (0.0165 to 0.0406)	0.0646*** (0.0475 to 0.0818)	0.0682*** (0.0445 to 0.0919)	-2.026*** (-2.464 to -1.588)	0.0940*** (0.0693 to 0.119)	0.0789*** (0.0569 to 0.101)	-0.641*** (-0.748 to -0.535)	0.0902*** (0.0444 to 0.136)
Activity mix Work	0.177*** (0.153 to 0.201)	-0.0239 (-0.0875 to 0.0398)	0.114*** (0.0560 to 0.173)	0.565*** (0.172 to 0.959)	0.199*** (0.105 to 0.292)	0.182*** (0.149 to 0.215)	0.348*** (0.258 to 0.438)	0.0710 (-0.0712 to 0.213)
Pct Walk/Bike Work (census)	-0.0118*** (-0.0188 to -0.00488)	0.0251*** (0.0123 to 0.0380)	0.0271*** (0.0149 to 0.0394)	-1.194*** (-1.530 to -0.859)	-0.0651*** (-0.0992 to -0.0309)	0.00132 (-0.00778 to 0.0104)	-0.161*** (-0.204 to -0.118)	-0.0607*** (-0.105 to -0.0164)
Road Density Work	-0.0265** (-0.0490 to -0.00392)	-0.371*** (-0.438 to -0.304)	-0.188*** (-0.240 to -0.137)	-0.339 (-1.060 to 0.382)	0.148*** (0.104 to 0.192)	0.00979 (-0.0218 to 0.0414)	-0.338*** (-0.491 to -0.184)	0.0570 (-0.0390 to 0.153)
Observations	44,987	8,620	9,537	768	4,069	16,925	3,391	1,677
Observations with Zero VMT (telecommuters)	3,309	566	600	336	223	768	693	123
R2: MZ1	0.090	0.092	0.101	0.656	0.192	0.079	0.348	0.167

Robust 95% Confidence Intervals in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 29: Urban Low Transit Use

	Marginal Effects			Elasticities		
INDEPENDENT VARIABLES	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**
Number of Vehicles	3.586*** (1.722 to 5.451)	NS	NS	0.144*** (0.0692 to 0.219)	NS	NS
Income ($10,000)	0.634** (0.0323 to 1.235)	NS	NS	NS	NS	NS
Local Gasoline Price (cons. $)	-1.815*** (-2.888 to -0.743)	-0.549* (-1.156 to 0.0577)	NS	-0.113*** (-0.179 to -0.0462)	-0.0722* (-0.152 to 0.00759)	NS
Transit Access (census-based)	NS	-0.150** (-0.296 to -0.00341)	NS	NS	-0.0261** (-0.0517 to -0.000517)	NS
Jobs Access 0-5 miles, grav.	-0.473*** (-0.635 to -0.311)	-0.205*** (-0.303 to -0.108)	-0.214*** (-0.266 to -0.163)	-0.131*** (-0.177 to -0.0857)	-0.105*** (-0.156 to -0.0548)	-0.203*** (-0.253 to -0.153)
Jobs Access 5-50 miles, grav.	-0.336*** (-0.589 to -0.0827)	NS	NS	-0.194*** (-0.341 to -0.0477)	NS	NS
Activity mix	NS	NS	NS	NS	NS	NS
Perc. Walk/Bike (census-based)	NS	NS	NS	NS	NS	NS
Road Density	-0.198* (-0.419 to 0.0236)	NS	NS	-0.0741* (-0.157 to 0.00897)	NS	NS
Perc. Single Family Homes	NS	NS	NS	NS	NS	NS
Pct Transit Use Work (census)			0.137*** (0.0995 to 0.174)			0.0646*** (0.0475 to 0.0818)
Activity mix Work			NS			NS
Pct Walk/Bike Work (census)			0.0469*** (0.0221 to 0.0717)			0.0251*** (0.0123 to 0.0380)
Road Density			-0.310*** (-0.363 to -0.258)			-0.371*** (-0.438 to -0.304)

Table 30: Suburb With Multi-Family Housing

	Marginal Effects			Elasticities		
INDEPENDENT VARIABLES	Household Weekday	Individual Weekday Nonwork	Individual Weekday Commute	Household Weekday	Individual Weekday Nonwork	Individual Weekday Commute
Number of Vehicles	3.643*** (1.799 to 5.488)	NS	NS	0.138*** (0.0682 to 0.208)	NS	NS
Income ($10,000)	1.741*** (1.022 to 2.459)	0.890*** (0.471 to 1.309)	0.261** (0.0589 to 0.463)	0.171*** (0.0935 to 0.248)	0.178*** (0.0834 to 0.273)	0.0929* (-0.00461 to 0.190)
Local Gasoline Price (cons. $)	-1.622*** (-2.603 to -0.641)	-0.725** (-1.339 to -0.110)	-0.589*** (-0.946 to -0.231)	-0.102*** (-0.163 to -0.0407)	-0.0924** (-0.170 to -0.0148)	-0.123*** (-0.198 to -0.0481)
Transit Access (census-based)	-0.454*** (-0.674 to -0.235)	-0.107* (-0.216 to 0.00190)	NS	-0.0550*** (-0.0818 to -0.0281)	-0.0260* (-0.0524 to 0.000523)	NS
Jobs Access 0-5 miles, grav.	-1.025*** (-1.332 to -0.719)	-0.392*** (-0.566 to -0.219)	-0.401*** (-0.497 to -0.306)	-0.126*** (-0.164 to -0.0872)	-0.0914*** (-0.132 to -0.0505)	-0.168*** (-0.208 to -0.127)
Jobs Access 5-50 miles, grav.	0.228*** (0.0743 to 0.382)	NS	NS	0.0663*** (0.0217 to 0.111)	NS	NS
Activity mix	-2.959* (-6.481 to 0.563)	-2.044** (-4.024 to -0.0642)	NS	NS	-0.0421** (-0.0828 to -0.00140)	NS
Perc. Walk/Bike (census-based)	NS	NS	-0.110*** (-0.169 to -0.0507)	NS	NS	-0.0313*** (-0.0486 to -0.0140)
Road Density	-0.468*** (-0.732 to -0.204)	-0.170** (-0.304 to -0.0363)	-0.106** (-0.188 to -0.0242)	-0.154*** (-0.242 to -0.0656)	-0.108** (-0.194 to -0.0224)	-0.117** (-0.207 to -0.0261)
Perc. Single Family Homes	NS	NS	0.0137** (0.000601 to 0.0269)	NS	NS	0.0513** (0.00275 to 0.0998)
Pct Transit Use Work (census)			0.156*** (0.100 to 0.212)			0.0682*** (0.0445 to 0.0919)
Activity mix Work			2.291*** (1.121 to 3.461)			0.114*** (0.0560 to 0.173)
Pct Walk/Bike Work (census)			0.0602*** (0.0320 to 0.0883)			0.0271*** (0.0149 to 0.0394)
Road Density			-0.205*** (-0.260 to -0.150)			-0.188*** (-0.240 to -0.137)

Table 31: Central City

	Marginal Effects			Elasticities		
INDEPENDENT VARIABLES	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**
Number of Vehicles	17.60*** (8.723 to 26.48)	9.574*** (5.944 to 13.20)	NS	0.835*** (0.415 to 1.255)	1.109*** (0.703 to 1.515)	NS
Income ($10,000)	NS	NS	NS	NS	NS	NS
Local Gasoline Price (cons. $)	NS	NS	NS	NS	NS	NS
Transit Access (census-based)	-0.225** (-0.436 to -0.0137)	NS	NS	-0.579** (-1.122 to -0.0351)	NS	NS
Jobs Access 0-5 miles, grav.	NS	-0.172* (-0.370 to 0.0255)	NS	NS	-0.830* (-1.750 to 0.0912)	NS
Jobs Access 5-50 miles, grav.	NS	-2.006*** (-3.318 to -0.694)	NS	NS	-3.249*** (-5.318 to -1.180)	NS
Activity mix	NS	NS	NS	NS	NS	NS
Perc. Walk/Bike (census-based)	NS	NS	NS	NS	NS	NS
Road Density	NS	NS	NS	NS	0.893* (-0.157 to 1.942)	NS
Perc. Single Family Homes	NS	NS	NS	NS	NS	NS
Pct Transit Use Work (census)			-0.280*** (-0.335 to -0.224)			-2.026*** (-2.464 to -1.588)
Activity mix Work			3.766*** (1.202 to 6.329)			0.565*** (0.172 to 0.959)
Pct Walk/Bike Work (census)			-0.149*** (-0.186 to -0.112)			-1.194*** (-1.530 to -0.859)
Road Density Work			NS			NS

Table 32: Rural

	Marginal Effects			Elasticities		
INDEPENDENT VARIABLES	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**
Number of Vehicles	3.565*** (1.342 to 5.789)	NS	NS	0.135*** (0.0514 to 0.219)	NS	NS
Income ($10,000)	1.717*** (0.588 to 2.847)	NS	NS	0.105** (0.0167 to 0.193)	NS	NS
Local Gasoline Price (cons. $)	NS	-1.198* (-2.536 to 0.141)	NS	NS	-0.0978* (-0.207 to 0.0115)	NS
Transit Access (census-based)	NS	NS	-0.738*** (-1.014 to -0.462)	NS	NS	-0.0617*** (-0.0864 to -0.0371)
Jobs Access 0-5 miles, grav.	-2.272** (-4.228 to -0.316)	-2.553*** (-3.607 to -1.499)	-1.031*** (-1.618 to -0.444)	-0.0320** (-0.0600 to -0.00406)	-0.0588*** (-0.0838 to -0.0338)	-0.0541*** (-0.0857 to -0.0224)
Jobs Access 5-50 miles, grav.	1.916*** (1.317 to 2.515)	0.690*** (0.311 to 1.070)	0.417*** (0.220 to 0.615)	0.104*** (0.0730 to 0.135)	0.0615*** (0.0285 to 0.0946)	0.0827*** (0.0447 to 0.121)
Activity mix	-9.687** (-17.44 to -1.935)	-5.236** (-10.34 to -0.132)	-7.556*** (-10.24 to -4.869)	-0.0910** (-0.164 to -0.0177)	-0.0737** (-0.146 to -0.00118)	-0.245*** (-0.333 to -0.156)
Perc. Walk/Bike (census-based)	NS	0.245** (0.0371 to 0.453)	NS	NS	0.0325** (0.00549 to 0.0595)	NS
Road Density	-1.174*** (-1.802 to -0.547)	-1.740*** (-2.183 to -1.296)	-0.358*** (-0.597 to -0.119)	-0.0640*** (-0.0985 to -0.0296)	-0.143*** (-0.179 to -0.106)	-0.0650*** (-0.109 to -0.0208)
Perc. Single Family Homes	0.139*** (0.0532 to 0.224)	NS	0.0679*** (0.0390 to 0.0969)	0.189*** (0.0727 to 0.305)	NS	0.315*** (0.183 to 0.448)
Pct Transit Use Work (census)			0.731*** (0.523 to 0.939)			0.0940*** (0.0693 to 0.119)
Activity mix Work			5.281*** (2.775 to 7.787)			0.199*** (0.105 to 0.292)
Pct Walk/Bike Work (census)			-0.149*** (-0.224 to -0.0740)			-0.0651*** (-0.0992 to -0.0309)
Road Density Work			0.378*** (0.263 to 0.492)			0.148*** (0.104 to 0.192)

Table 33: Suburb With Single-Family Housing

	Marginal Effects			Elasticities		
INDEPENDENT VARIABLES	Household Weekday	Individual Weekday Nonwork	Individual Weekday Commute	Household Weekday	Individual Weekday Nonwork	Individual Weekday Commute
Number of Vehicles	1.842** (0.0398 to 3.644)	NS	NS	0.0635** (0.00138 to 0.126)	NS	NS
Income ($10,000)	1.654*** (1.064 to 2.244)	NS	0.203*** (0.0521 to 0.355)	0.134*** (0.0756 to 0.192)	NS	0.0580* (-0.00497 to 0.121)
Local Gasoline Price (cons. $)	-2.148*** (-3.120 to - 1.176)	-0.796*** (-1.307 to - 0.286)	NS	-0.0969*** (-0.141 to - 0.0532)	-0.0857*** (-0.141 to - 0.0308)	NS
Transit Access (census-based)	-0.350*** (-0.574 to - 0.126)	-0.151*** (-0.242 to - 0.0605)	-0.142*** (-0.225 to - 0.0587)	-0.0202*** (-0.0333 to - 0.00714)	-0.0216*** (-0.0347 to - 0.00851)	-0.0299*** (-0.0475 to - 0.0123)
Jobs Access 0-5 miles, grav.	-2.407*** (-2.877 to - 1.937)	-0.741*** (-0.934 to - 0.548)	-0.936*** (-1.073 to - 0.798)	-0.119*** (-0.143 to - 0.0952)	-0.0852*** (-0.108 to - 0.0628)	-0.162*** (-0.193 to - 0.131)
Jobs Access 5-50 miles, grav.	0.192* (-0.0117 to 0.396)	NS	NS	0.0344* (-0.00206 to 0.0708)	NS	NS
Activity mix	NS	NS	NS	NS	NS	NS
Perc. Walk/Bike (census-based)	-0.496*** (-0.750 to - 0.242)	-0.156*** (-0.267 to - 0.0443)	-0.122** (-0.219 to - 0.0254)	-0.0200*** (-0.0305 to - 0.00955)	-0.0135*** (-0.0233 to - 0.00376)	-0.0161** (-0.0296 to - 0.00265)
Road Density	-0.418*** (-0.626 to - 0.211)	-0.306*** (-0.394 to - 0.217)	-0.0874** (-0.166 to - 0.00917)	-0.0596*** (-0.0894 to - 0.0298)	-0.100*** (-0.130 to - 0.0707)	-0.0432** (-0.0859 to - 0.000476)
Perc. Single Family Homes	0.0562** (0.00558 to 0.107)	0.0225* (-6.73e-05 to 0.0452)	0.0257*** (0.00950 to 0.0419)	0.0795** (0.00806 to 0.151)	0.0738* (-5.00e-05 to 0.148)	0.125*** (0.0492 to 0.201)
Pct Transit Use Work (census)			0.234*** (0.183 to 0.285)			0.0789*** (0.0569 to 0.101)
Activity mix Work			4.904*** (3.830 to 5.978)			0.182*** (0.149 to 0.215)
Pct Walk/Bike Work (census)			NS			NS
Road Density Work			NS			NS

Table 34: Urban With High Transit Use

	Marginal Effects			Elasticities		
INDEPENDENT VARIABLES	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**
Number of Vehicles	8.557** (0.433 to 16.68)	NS	NS	0.341** (0.0178 to 0.664)	NS	NS
Income ($10,000)	NS	0.475* (-0.0819 to 1.032)	NS	NS	NS	NS
Local Gasoline Price (cons. $)	-2.195*** (-3.831 to -0.559)	NS	-0.912*** (-1.484 to -0.341)	-0.203*** (-0.353 to -0.0520)	NS	-0.270*** (-0.440 to -0.101)
Transit Access (census-based)	-0.244*** (-0.386 to -0.103)	-0.151*** (-0.229 to -0.0725)	0.0440* (-0.00406 to 0.0920)	-0.205*** (-0.326 to -0.0850)	-0.286*** (-0.436 to -0.136)	0.117* (-0.0107 to 0.244)
Jobs Access 0-5 miles, grav.	NS	NS	NS	NS	NS	NS
Jobs Access 5-50 miles, grav.	NS	NS	NS	NS	NS	NS
Activity mix	NS	NS	-3.423*** (-5.389 to -1.456)	NS	NS	-0.144*** (-0.229 to -0.0600)
Perc. Walk/Bike (census-based)	-0.217** (-0.387 to -0.0472)	-0.139*** (-0.211 to -0.0662)	-0.0902*** (-0.159 to -0.0218)	-0.0706** (-0.128 to -0.0130)	-0.0953*** (-0.146 to -0.0443)	-0.0903** (-0.162 to -0.0186)
Road Density	NS	NS	NS	NS	NS	NS
Perc. Single Family Homes	NS	-0.0306** (-0.0554 to -0.00579)	-0.0182* (-0.0380 to 0.00162)	NS	-0.0848** (-0.154 to -0.0155)	-0.0715* (-0.150 to 0.00702)
Pct Transit Use Work (census)			-0.285*** (-0.328 to -0.242)			-0.641*** (-0.748 to -0.535)
Activity mix Work			5.169*** (3.777 to 6.561)			0.348*** (0.258 to 0.438)
Pct Walk/Bike Work (census)			-0.0864*** (-0.108 to -0.0652)			-0.161*** (-0.204 to -0.118)
Road Density Work			-0.182*** (-0.265 to -0.0995)			-0.338*** (-0.491 to -0.184)

Table 35: Rural-In-Urban

	Marginal Effects			Elasticities		
INDEPENDENT VARIABLES	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**	**Household Weekday**	**Individual Weekday Nonwork**	**Individual Weekday Commute**
Number of Vehicles	3.988** (0.427 to 7.548)	NS	NS	0.155** (0.0168 to 0.292)	NS	NS
Income ($10,000)	NS	NS	NS	NS	NS	NS
Local Gasoline Price (cons. $)	NS	NS	-1.343** (-2.676 to -0.00969)	NS	NS	-0.257** (-0.509 to -0.00388)
Transit Access (census-based)	-0.986*** (-1.673 to -0.299)	-0.544*** (-0.957 to -0.130)	-0.535*** (-0.887 to -0.182)	-0.0483*** (-0.0825 to -0.0140)	-0.0408*** (-0.0716 to -0.0100)	-0.0830*** (-0.141 to -0.0249)
Jobs Access 0-5 miles, grav.	-1.242* (-2.631 to 0.147)	-0.741*** (-1.182 to -0.300)	-1.045*** (-1.568 to -0.522)	-0.0460* (-0.0993 to 0.00726)	-0.0437*** (-0.0702 to -0.0173)	-0.117*** (-0.179 to -0.0541)
Jobs Access 5-50 miles, grav.	1.612*** (0.816 to 2.407)	0.779*** (0.225 to 1.334)	0.494*** (0.150 to 0.838)	0.132*** (0.0695 to 0.194)	0.103*** (0.0327 to 0.173)	0.125*** (0.0393 to 0.210)
Activity mix	NS	NS	NS	NS	NS	NS
Perc. Walk/Bike (census-based)	NS	NS	NS	NS	NS	NS
Road Density	NS	NS	NS	NS	NS	NS
Perc. Single Family Homes	0.0993* (-0.0123 to 0.211)	0.0762* (-0.00259 to 0.155)	NS	0.122* (-0.0136 to 0.258)	0.153* (-0.00138 to 0.307)	NS
Pct Transit Use Work (census)			0.518*** (0.238 to 0.797)			0.0902*** (0.0444 to 0.136)
Activity mix Work			NS			NS
Pct Walk/Bike Work (census)			-0.123*** (-0.209 to -0.0370)			-0.0607*** (-0.105 to -0.0164)
Road Density Work			NS			NS

DISCUSSION

Here we interpret the results for models of Total Household VMT, Individual Nonwork VMT, and Individual Home-To-Work Commute VMT that are reported in Table 20 through Table 28, discuss how they compare to the previous literature, and highlight their implications for policy.

Sign and Significance

The sign and significance pattern of the estimated coefficients (Table 20, Table 23, and Table 26) is consistent with past research. At the household level,VMT is higher with more vehicles and higher income. The effect of income is quadratic, as indicated by the negative signs on income squared. Households with more workers have higher VMT. Individuals who work, however, have lower nonwork VMT. Among workers, those who work only part time have shorter commutes. These results are rather consistent across the neighborhood types (in terms of sign and significance) with limited exceptions. In some cases, coefficients on these demographic variables in the household VMT model are statistically insignificant in the "Central City" and "Rural In Urban" neighborhood types – the two neighborhood types with the smallest number of observations – but the broader pattern is one of consistent and expected impacts of the demographic variables.

The turning point for the quadratic effect of income on VMT in all three full sample models is at $175,000 per year. For the household model, the effect of higher income on VMT turns negative at annual incomes ranging from $170,000 to $179,000 in all neighborhood types where the income coefficients are statistically significant except "Rural" where the effect of income on VMT turns negative at $147,000 per year. In general, these are high income levels. As a practical matter, policy makers would do well to recognize that household VMT increases with income at all but the highest income levels. In contrast, individual VMT – at least when divided into commute and nonwork trip purposes – is less universally sensitive to income across neighborhood types.

Households have higher VMT in spring and summer, and while there are day-of-week effects indicating that daily weekday VMT is lower on Mondays than on other weekdays, we do not believe there are policy relevant implications of that finding.

Turning to the land use and price variables, higher gas prices are associated with less VMT, as would be expected. The estimated effects are larger for the household VMT model than in either the nonwork VMT model or the home-to-work commute VMT model, but the gas price effect is negative and statistically significant for many neighborhood types in all three models. This indicates, as expected, that gas prices can have an impact on all types of travel, especially in neighborhood types where alternatives to the private vehicle are available.

Where statistically significant, transit access in the home census tract is associated with reduced VMT for households and for nonwork trips, but its effect is somewhat mixed for home-to-work commute VMT. Pedestrian and bicycle-friendliness at home has a negative impact on all types of VMT as well.

When looking at the effect of both of these variables measured at the work location in the home-to-work commute VMT model, we see a different set of effects. The overall effect is positive for transit access and negative for pedestrian and bicycle friendliness, but it is mixed depending on neighborhood type. The explanation we offer is the following. Transit access at the work location is serving at least partially as an indicator of whether the work location is centrally located (e.g. in the regional central business district). Since so many jobs are now dispersed, the overall positive coefficient may indicate that those who travel to major job and transit centers for work are more likely to have longer commutes. The pattern of signs on the estimated coefficients for work location transit access among the neighborhood types follows this interpretation, with negative estimated coefficients for those who live in high transit neighborhood types and positive estimated coefficients for those who do not. Estimated coefficients on the activity mix at the work location follow this same pattern.

The two job access variables reflect an interesting pattern that we believe is largely untested in the literature. Job access is measured by two variables – a gravity measure of the number of jobs within five miles of a household and a gravity measure of job accessibility from 5 to 50 miles from the household. In the full sample, the number of jobs within five miles is associated with lower VMT while the number of jobs beyond five miles (the gravity variable) is associated with higher VMT. This pattern largely persists in the regressions by neighborhood type as well as in the individual regressions explaining nonwork and home-to-work commute VMT, with some exceptions where these variables are statistically insignificant. As expected, the jobs access variables – especially the more local job access variable – have a larger effect on home-to-work commute VMT than on nonwork VMT.

Overall, we note two points. First, the literature has, to our knowledge, not tested the effect of nearby versus more distant jobs, and in our regressions we find evidence that nearby job access (five miles or less) is associated with less driving while, as one would expect, increases in job availability beyond five miles is associated with more driving. Second, these effects are more robust in suburban neighborhoods. Both job access variables are insignificant in the "central city" and "Urban High Transit Use" neighborhood types, likely because job access in those most urbanized of places in the state is high already and increases in job access there, at the margin, may not reduce VMT. (Note that this finding is consistent with the results in Boarnet et al., 2011, who found that a gravity measure of employment accessibility was not statistically significantly associated with VMT in the highest employment accessibility quartile in the Los Angeles metropolitan area.)

Marginal Effects and Elasticities

Table 22, Table 25, and Table 28 show the elasticities that are implied by the coefficients and tobit marginal effects. The first five variables in that table – number of vehicles in the household, household income and its square, the number of employed workers in the household, and household size – are sociodemographic rather than land use characteristics. Consistent with previous research, we find that the largest impact on VMT is from those sociodemographic variables, though some land use variables have comparably-sized effects. The magnitude of the effect of those sociodemographic variables, with only a few exceptions, does not vary much across the neighborhood types. The exceptions are the large elasticity of VMT with respect to vehicle ownership in "Central City" neighborhoods (0.8), the insignificant effect of vehicle ownership on VMT in "Urban High Transit Use" neighborhoods, the insignificant effect of income on VMT in "Central City" neighborhoods, and the larger effect size of income in the two neighborhood types that house the poorest households ("Urban High Transit Use" and "Suburb with Multifamily Housing"). We believe those variations might reflect the possibility that car ownership is quite common in the suburbs, while in central cities there may be substantial scope to discourage driving by discouraging car ownership.

However, inferences about the effect of reducing vehicle ownership on VMT, interpreted from our results, should be viewed with caution for three reasons. First, the "Central City" neighborhood type includes only relatively small areas in the most urbanized portions of the state's major cities, suggesting that only in a small number of locales might reducing car ownership be a fruitful way to reduce VMT. Second, we did not model vehicle ownership as an endogenous choice variable. Finally, vehicle ownership, income, and household size are highly correlated with each other, making it difficult to be confident which of these variables is the true "driver" of VMT change. Because our interest is in estimating the effect of land use and transport system variables on VMT, however, we do not need to be concerned about this multicollinearity. Including all of these demographic variables in our analysis should effectively control for their effects so that we can be sure that differences in population demographics between neighborhood types are not confounding our estimates of the effects we care most about.

The elasticity of household VMT with respect to gas price is -0.10 in the full sample, essentially the same estimate that Small and van Dender (2007) obtained using entirely different data aggregated to the state level. The gas price elasticity of household VMT, when statistically significant, does not vary much with the exception of the -0.20 elasticity in the "Urban High Transit Use" neighborhood type. Gas price is statistically insignificant in the "Central City", "Rural", and "Rural In Urban" neighborhood types. At first glance, this may seem counter-intuitive, but we posit that this finding reflects an important reality. Gas price increases will not have a significant impact on VMT for people who are already minimizing their driving. In the case of "Central City" dwellers, driving is inconvenient and they have many alternatives for most trips. This means that trips for which they use their cars are not flexible in some way. In the case of "Rural" residents, they are already minimizing their driving by trip chaining and trip reduction where possible because of the time and money cost of each trip.

For the places "in the middle", the VMT response to increases in gas prices are quite similar across neighborhood types. Note that the elasticity is especially high in the "Urban High Transit Use" neighborhood type, but this is because the average VMT for these households is low – not because the estimate marginal effect is larger. We expect that this pattern of results that we observe for gas prices should hold for any VMT pricing, including road pricing or a direct VMT tax. It may also be somewhat indicative of where parking pricing policies are likely to have the greatest effect on VMT.

Interestingly, this household model result is echoed fully in the home-to-work commute VMT model, but not in the nonwork VMT model. Where statistically significant, the estimated elasticity of nonwork VMT with respect to gasoline price is nearly the same magnitude across neighborhood types, and less than -0.10. This may mean that much of the VMT sensitivity to gas prices that we see could be due to commute mode switching where this is a viable option and not as much due to overall reduction in VMT for other trip purposes (for which transit is often a less attractive alternative).

Table 36: Definitions for Dependent and Key Independent Variables, Including Units

Household VMT: UNIT=MILES. Sum of weekday daily Vehicle Miles Traveled generated by all members of a household. Trips made in the same vehicle by multiple household members are counted only once.
Nonwork VMT: UNIT=MILES. Sum of weekday daily Vehicle Miles Traveled for nonwork purposes generated by one adult.
Home-To-Work Commute VMT: UNIT=MILES. Direct network distance between home and work for one adult.
Percent of Commuters Using Transit: UNIT=1 PERCENT. Percent of commuters who used transit to get to work based on census journey-to-work data.
Percent of Housing Units that are Single Family Homes: UNIT=1 PERCENT. Census-based.
Road Density: UNIT=KM OF ROAD PER SQUARE KM. Road kilometers per square kilometer of land for each census tract. Note that this is not lane-kilometers; multi-lane highway kilometers and side street kilometers are counted as the same.
Activity Mix: UNIT=INDEX BETWEEN 0 AND 1. Entropy index between 0 and 1 that indicates how mixed the activities in the census tract are. The activities included in the index are residential population and the number of jobs in each of four categories – industrial jobs, retail jobs, office jobs, and public sector jobs.
Regional Job Access: UNIT=10,000 DISTANCE-WEIGHTED JOBS. Distance-weighted sum of the number of jobs located between 5 and 50 miles of the census tract.
Local Job Access: UNIT=10,000 DISTANCE-WEIGHTED JOBS. Distance-weighted sum of the number of jobs located between 0 and 5 miles of the census tract.
Percent of Commuters Using Non-Motorized Modes: UNIT=1 PERCENT. Percent of commuters who walked or biked to work based on census journey-to-work data.
Average Gasoline Price in 2000: UNIT=JANUARY 2013 DOLLARS. Based on Oil Price Information Service data by zip code for 2005 together with US Department of Energy monthly data for 2000. Converted to January 2013 dollars using the Consumer Price Index.

The transit access elasticity of household VMT is highest in the "Central City" and "Urban High Transit Use" neighborhood types (-0.58 and -0.20, respectively), and 0.05 or below in magnitude elsewhere. This variation in the estimated elasticity of VMT with respect to transit access has less to do with a real difference in effect than it has to do with the fact that the percent of commuters using transit varies substantially between neighborhood types. The mean value of this transit access variable is much higher in the "Central City" and "Urban High Transit Use" areas than it is in the rest of the state (0.34 and 0.22, compared to 0.05 or less elsewhere – see

Table 37. Looking at the marginal effects of transit access on household VMT listed in Table 21, we see that in fact, the effect of a one percentage point increase in the percent of commuters who use transit is actually quite comparable across neighborhood types, with the highest point estimates appearing in the "Suburb MFH" and "Rural-In-Urban" neighborhood types.

Table 37: Average Values of Key Land Use and Transport System Variables for Each Neighborhood Type

	Act. Mix	Pct. Walk or Bike Commute	Pct. Transit Commute	Pct. SFH	Local Job Access (Gravity 0-5 Miles)	Regional Job Access (Gravity 5-50 Miles)	Gas Price Jan 2000	Road Density (km/km^2)
Urban Low Transit Use	0.41	3%	4%	59%	9.55	27.52	$1.89	14.8
Suburb MFH	0.39	4%	5%	47%	4.61	13.55	$1.88	13.1
Central City	0.53	20%	35%	5%	35.55	12.70	$1.95	19.1
Rural	0.43	4%	1%	65%	0.39	2.69	$1.94	2.6
Suburb SFH	0.37	2%	2%	81%	2.07	10.22	$1.89	7.8
Urban High Transit Use	0.28	6%	21%	29%	14.72	26.31	$1.91	17.1
Rural-In-Urban	0.46	6%	2%	52%	1.23	3.33	$1.92	7.3
Total	0.39	4%	5%	58%	5.97	16.02	$1.90	11.5

Note that this example highlights the difference in interpretation between elasticities and marginal effects. Elasticities control for scale of variables, and are therefore a good way to compare the effect sizes of different independent variables on a dependent variable for a single dataset. However, when comparing elasticities across datasets (or, in this case, different subsets from the same data), it is important to also compare the mean values of the independent and dependent variables of interest. Elasticities can be highly misleading if used to compare results for populations that have large differences in the independent or the dependent variable for which the elasticity is being calculated.

We next consider the effect of jobs within file miles on household VMT. The elasticity of the five-mile job access variable is highest in the "Urban Low Transit Use", "Suburb MFH", and "Suburb SFH" neighborhood types, all estimated to be approximately -0.12. Those elasticities are on the low-end of effects in the literature. Salon et al. (2012, Table 2) found regional job access gravity variables had VMT elasticities from -0.13 to -0.25 in their review. The finding that the job access elasticity varies across neighborhood types and is largest in the "Urban Low Transit Use" and both suburban neighborhood types generally agrees with Boarnet et al. (2011), who found that job access was significant in the middle ranges of access (and hence of urbanization) in the greater Los Angeles region. We note, though, that the results here do not indicate job access elasticities as large as those found by Boarnet et al. (2011) which in some cases approached -1.0.

Again, it is instructive to also look at the estimated marginal effects of job access to see a fuller picture. When we do this, we see that the largest marginal effect on household VMT with a set increase in local jobs is actually in the “Rural” neighborhood type, followed by the two suburban neighborhood types.

The activity mix elasticity of household VMT is only significant in the full sample (at -0.03) and in the “Rural” neighborhood type (at -0.09), which spans the range found in the Salon et al. (2012, Table 2) summary. The home location activity mix elasticity of nonwork and home-to-work commute VMT is estimated to be similar.

Road density may capture effects similar to the “network connectivity” measure summarized in Salon et al. (2012). (Note that network connectivity, in that review, is a measure of either road intersection density or road density.) The estimated elasticities with respect to road density from the full sample for our models of household, nonwork, and home-to-work commute VMT range between -0.15 and -0.19, consistent with the literature (Salon et al. 2012, Table 2.) This effect size is comparable to that calculated for some of the demographic variables that we included.

Policy Implications

As hypothesized, we find evidence that the effect of land use and transport system variables on VMT varies with the urban context. The effect of gas price changes on VMT is effectively zero in the “Central City”, “Rural” and “Rural In Urban” neighborhood types and substantial in all other neighborhood types. The effect of local employment access on VMT is larger in the “Urban Low Transit Use”, “Suburb MFH”, and “Suburb SFH” neighborhood types. Combined, these results suggest that the effect of prices on driving will be largest where persons have alternatives to driving and/or flexibility to increase trip chaining and consolidate travel to reduce overall VMT. Looking forward, as California continues to experiment with congestion pricing and parking pricing, policy-makers should note that such pricing tools will likely do more to reduce VMT in places where persons are not already minimizing auto travel. Based on the results in this report, we believe that increasing the cost of driving (through, e.g., more efficient pricing) and providing alternatives to driving are not either/or substitutable policies, but rather complementary policies that combined can have larger impacts in terms of system efficiencies and externality reduction than would be possible separately.

Employment access is an important predictor of driving, particularly so for jobs within five miles of residents in suburban areas and in the least urbanized of the “urban” neighborhood types (“Urban Low Transit Use”.) In those relatively suburban locales, land use policy would fruitfully focus on increasing access to nearby (within five miles) jobs, and the effect of such policies on VMT would be larger than focusing only on activity mix or residential density.

To put these results in the context of AB32 and SB375, we performed a rough policy scenario analysis, where we imagined that reasonable changes were made in the most important variables that influence VMT for each neighborhood type. This scenario analysis is meant to be suggestive of the order of magnitude of the total impact of these sorts of land use-transport system changes on VMT. We used our own judgement to identify "reasonable" changes in the variables. We expect that even these changes may not actually be feasible in some actual neighborhoods, while other actual neighborhoods would be able to make much larger changes. In this scenario analysis, census tracts did not actual switch from one neighborhood type to another. The goal here is to generate a rough estimate of how much changes in the land use and transport system *within each neighborhood type* could affect VMT.

Table 38: Rough Scenario Analysis Assumptions and Calculations

NH Type	Households (millions, 2000 Census)	Mean HH weekday VMT	Local Jobs Access	Transit Use	Bike Ped Use	Road Density[h]	Gas Price[i]	Effect Total (sum)
Urban Low Transit Use	2.90	41.6	-0.473[a]				-1.815	-2.3
Suburb MFH	3.05	41.6	-1.025[a]				-1.622	-2.6
Central City	0.18	16.8		-1.125[c]				-1.1
Rural	0.98	50.1	-1.136[b]			-1.174		-2.3
Suburb SFH	2.82	58.8	-1.204[b]	-1.05[d]	-0.992[f]		-2.148	-5.4
Urban High Transit Use	1.04	28.8		-0.732[d]	0.651[g]		-2.195	-2.3
Rural In Urban	0.50	41.7	-0.621[b]	-0.986[e]			-1.815	-1.6

a. Increase distance-weighted sum of jobs within 5 miles of home by 10,000.
b. Increase distance-weighted sum of jobs within 5 miles of home by 5,000.
c. Increase transit commuting by 5 percentage points.
d. Increase transit commuting by 3 percentage points.
e. Increase transit commuting by 1 percentage point.
f. Increase walk and bicycle commuting by 2 percentage points.
g. Increase walk and bicycle commuting by 3 percentage points.
h. Increase road density by 1 km per km^2.
i. Increase gas price (or similar pricing strategy such as VMT pricing) by the equivalent of $1 per gallon.

Table 38 outlines the scenario itself, along with our estimate of how much each aspect of the scenario would reduce VMT. With the exception of the first column which indicates how many households were reported to live in each neighborhood type, all of the numbers in the table are in the units of household weekday VMT. For this rough analysis, we make the simplifying assumption that the effects of land use and transport system changes on VMT will be simply additive. It may be that interactions between changes would lead to larger or smaller overall changes than are predicted by the simple sum. Again, this scenario analysis is meant to be suggestive of the order of magnitude of the total effect size.

The overall result of this rough scenario analysis is that if all of these variables were changed in the neighborhood types indicated in Table 38, the total effect on household weekday VMT would be to reduce it by about 7 percent. It is worth noting that, given the particular parameters of this scenario, approximately half of this total effect is due to changes in the price of driving.

An important point that arose in the process of doing this project was the lack of a direct connection between the variables included in our analysis and specific actions that local and regional governments can take to reduce VMT. To the extent that policy-sensitive variables are not the same as implementable policies, however, our results are somewhat less directly useful for decision making than we'd like. We acknowledge that this is a shortcoming of our research, as it is a shortcoming of most of the related existing literature. In an attempt to begin to connect our results to real-world actions, we have created Table 39.

As is evident from Table 39, some of the land use and transport system variables included in our analysis point directly to one or two local actions; in these cases, the relationship between variable and action is clear. However, many of the variables we include in our model could be affected by multiple local actions. In these cases, we expect that there will be variation among communities both in which local actions will be most effective at changing these variables and also in which local actions are politically palatable to the community. For instance, many of the relevant local actions are to allow and incentivize certain types of development in certain locations. However, we would expect that developers would respond more strongly to such land use regulatory changes in some communities than in others – presumably because the demand would be higher in these places and/or NIMBY resistance to denser development would be lower.

Based on this research, we cannot say which of the local actions to influence a particular variable will be most effective in a community. We can say, however, which variables are likely to have the largest impact on VMT in a community based on the current neighborhood types present. This contribution will – we hope – go a long way toward helping local decision makers narrow the set of possible actions to consider as they aim for a lower-VMT future.

Table 39: Correspondence between Analysis Variables and Local Actions

Variable	Example Policies
Gasoline Price	• Road pricing • Possibly parking pricing
Percent Riding Transit to Work	• Add transit routes • Increase service frequency (i.e. reduce headways) • Add real-time transit vehicle arrival information to stations and stops • Add premium (e.g. faster, more comfortable) service for an additional charge • Provide additional amenities (e.g. wi-fi access) on transit vehicles and at major transfer hubs
Gravity Measures of Job Access	• Incentivize development that brings housing to job centers and/or brings jobs to housing centers • Implement mixed-use zoning
Entropy Measure of Activity mix	• Implement mixed-use zoning
Percent Walking/Biking to Work	• Implement complete streets • Sidewalk and path construction and maintenance • Bicycle lane and path construction and maintenance • Create bicycle boulevards • Implement road diets to improve pedestrian safety • Implement traffic calming measures • Improve pedestrian crossings • Implement mixed-use zoning • Incentivize infill development
Road Density	• Improve connected-ness of road network
Percent Single Family Homes	• Allow multifamily housing development

SUMMARY AND CONCLUSIONS

To comply with AB 32 and SB 375, California local and regional governments are working to develop and implement new policies that aim to reduce vehicle miles traveled (VMT). To develop targeted policies with scarce resources, cities, counties, and regions need guidance as to which policies will be most effective. The challenge is that the particulars of the local and regional context play a large role in determining which actions will be most effective where, but existing research provides little evidence on how context affects policy effectiveness. This project begins to fill this gap in the literature by estimating how the elasticities and marginal effects of policy-sensitive variables differ across trip purposes and local contexts.

The research goal of this project was to explore heterogeneity in how much Californians will change the amount that they drive in response to changes in land use and transport system characteristics. We explored this heterogeneity across two important dimensions – neighborhood type and trip type – and used statistical analysis of travel survey and land use data to quantify these relationships. We controlled for key household and individual demographic characteristics and characteristics of the surveys themselves. We also controlled for household selection of residential neighborhood type. As part of this work, we also estimated the difference in average VMT for three categories of VMT and seven distinct neighborhood types.

Our main analysis consisted of three steps. First, we used quantitative methods to classify census tracts into seven neighborhood types. Second, we estimated a multinomial logit model (MNL) of household choice of which neighborhood type to live in. Finally, we estimated tobit models of household weekday VMT, commute VMT for adult workers, and nonwork VMT for all adults for each neighborhood type. These models are the basis for calculation of the marginal effects and elasticities that are the main results of this project.

The land use and transport system characteristics for which marginal effects and elasticities were estimated in this research were gasoline price, local job access, regional job access, transit access, pedestrian and bicycle friendliness, percent of housing that is single family detached, road density, and activity mix. All of the estimated effects of these variables on VMT have the expected signs and their magnitudes are broadly consistent with those found in previous studies.

We find that the effects of some land use and transport system characteristics do depend on neighborhood type, in ways that are intuitive but had not previously been empirically verified. A rough scenario analysis indicates that marginal infrastructure and pricing changes within neighborhood types will yield reductions in VMT and greenhouse gas emissions on the order of 5 percent. At a more basic level, we have also shown that there are large VMT differences between people living in different neighborhood types in California. Household daily weekday VMT and nonwork VMT are both three times larger in the highest-VMT neighborhood type than in the lowest. This ratio for home-to-work commute VMT is 2.5.

Taken together, these two findings point to a two-pronged VMT reduction strategy for local policymakers. First, to the extent that there is local demand for lower VMT neighborhood types, these neighborhoods should be made available. Doing this might entail offering incentives for people to move into them (e.g. location-efficient mortgages), and also removing barriers that make it difficult for developers to build them.

Second, within existing development patterns, strategies to reduce VMT should be tailored to the neighborhood type. Our findings show that pricing strategies will work best in the middle range of neighborhood types (urban-suburban, but not central city and not rural). This likely reflects the fact that residents of these neighborhood types have flexibility to choose to drive less when gas prices are high. The effect on VMT of improving job access likewise is highly variable across neighborhood types, with the largest absolute effect of local jobs seen in the "Rural" and "Suburb, Single Family Homes" neighborhood types, where current job access is somewhat limited. As expected, increasing road density is an important determinant of VMT only in areas with relatively lower road densities. Understanding these neighborhood-based differences in the effectiveness of policies to reduce VMT should substantially improve the success of efforts to comply with AB 32 and SB 375.

RECOMMENDATIONS

Given the available cross-sectional travel survey data, we have done the best that we can in this research project to gain a better understanding of the likely heterogeneity of VMT response to changes in land use and transport system characteristics while controlling at least partially for residential self-selection. However, much remains to be done to fully understand the relationship between policy, built environment characteristics, and VMT to help policymakers make the best choices they can.

In the published literature review that this research team took the lead in writing, we highlight five specific opportunities for future work. This project has taken a large step toward filling one of these gaps in the literature. The remaining four are:

1. Conducting analysis that focuses on understanding policy interaction effects, taking into account the fact that the effect of local actions on VMT will depend somewhat on which other local actions are taken simultaneously.
2. Conducting analysis that improves our understanding of causal relationships between factors and VMT by using experimental research designs – studying current policy "natural" experiments with before-after data collection and carefully selected control groups.
3. Improving base travel data through use, for example, of Geographic Positioning Systems (GPS).
4. Improving the links between the land use and transportation system variables that are commonly used in the literature and real-world policies.

Each of these is discussed more fully in the conclusion section of our full literature review in Appendix A.

In addition to providing recommendations for future research, we offer recommendations for improving travel surveys so that they include a few extra nuggets of information that would make future research results more robust. There are two basic categories of additional information that we believe would be extremely useful additions to basic travel survey data.

First, we recommend including questions that capture not only what respondents are doing now, but any recent life changes and associated travel behavior changes. This may not be relevant for all respondents, but it would be especially useful to know both current and past travel choices for people who experienced a major life change within a year or two of the survey date (e.g. recently moved, married, had a baby, divorced/widowed, or became empty-nesters). Major opportunities for travel behavior change happen when other aspects of life shift, so understanding these shifts and how they typically affect travel choices could be key for making effective policies.

Second, we recommend adding a relatively short list of attitudinal questions, ideally standardized across surveys. These questions should focus on attitudes about neighborhood types, transport modes, and the environment. If a standard set of attitudinal questions were included in every household travel survey, we'd start to get a time series of how those attitudes change over time, and of course how they differ by socioeconomic characteristics. Gathering information about people's travel choices together with information about their basic travel-related preferences would go a long way toward understanding how much policies might be able to affect behavior.

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Longitudinal Employer-Household Dynamics, US Census Bureau.

US 2000 Decennial Census, US Census Bureau.

LIST OF PUBLICATIONS PRODUCED

Salon, D., Boarnet, M. G., Handy, S., Spears, S., & Tal, G. (2012). How do local actions affect VMT? A critical review of the empirical evidence. *Transportation research part D: transport and environment*, 17(7), 495-508.

GLOSSARY OF TERMS, ABBREVIATIONS, AND SYMBOLS

Cluster analysis: numerical analysis to group objects into categories based on a specified set of their characteristics.

Elasticity: the percentage change in a dependent variable that is predicted when an independent variable increases by one percent.

Factor analysis: numerical analysis to transform a set of collinear variables into a smaller number of factor variables that are not collinear and still contain most of the same information as the original variables

GIS: Geographic Information Systems

Marginal effect: the change in the dependent variable that is predicted when an independent variable increases by one unit.

Multinomial logit: statistical analysis to explain and predict the choice between discrete and unordered alternatives in an outcome variable (e.g. transport mode choice).

Tobit: statistical analysis to explain and predict the choice of a continuous outcome variable which has a censored or truncated distribution, often at the value of zero.

VMT: Vehicle Miles Traveled

APPENDIX A: FULL TEXT OF PUBLISHED LITERATURE REVIEW: HOW DO LOCAL ACTIONS AFFECT VMT? A CRITICAL REVIEW OF THE EMPIRICAL EVIDENCE

Deborah Salon, Marlon G. Boarnet, Susan Handy, Steven Spears, Gil Tal

Abstract

In this paper, we present a discussion of the challenges for research on the topic of vehicle miles traveled. We then summarize and critique evidence from the US on the association between fourteen distinct factors and vehicle miles traveled. Our results quantify how much vehicle miles traveled can be expected to change in response to changes in policy or land use factors, including residential density and land use mix, as well as specific transport policies and programs such as transit improvements, road pricing, and programs aimed at changing people's travel choices. Overall, though individual studies differ as to exact effect sizes, it is clear that local-level policymakers can take actions that are likely to affect vehicle miles traveled. However, we highlight gaps in the knowledge base at a time when decision makers at the local level are being increasingly called upon to take action to reduce vehicle miles traveled. Variation in effect size based on local context or interaction with related policies and programs has been left largely unexplored. In addition, experimental research designs that can identify causal direction are rare, and appropriate data that quantifies vehicle miles traveled are often lacking.

Keywords: vehicle miles traveled; research design; transport pricing; transit; travel and the environment

INTRODUCTION

Reducing vehicle miles traveled (VMT) would generate many benefits. These include alleviating traffic congestion, reducing air pollution, reducing greenhouse gas emissions, reducing our dependence on foreign oil, improving public health through increased exercise, and enhancing interactions within our communities. A number of state governments – including California, Washington, and Florida – have recently passed legislation aiming to rein in VMT, and many cities have independently begun to take action to reduce VMT in their jurisdictions.

There are plenty of policy ideas for how to reduce VMT. Road and parking pricing, mixed use zoning, investments in alternative modes, and household travel planning programs represent just a small sample of the possibilities. These policies can be costly, they may require substantial political capital, and/or they may have an effect only over the long-run. Planners and local government officials aiming to affect VMT must choose among them. To choose wisely, it is necessary to know – in addition to its cost, likelihood of political acceptance, and any co-benefits – how much each policy option will actually affect VMT.

We identify the best available evidence of the size of the effect of a variety of factors that are influenced by public policy on VMT, and we highlight areas where this evidence is especially weak. We do not address the important and controversial question of whether VMT reduction is an appropriate target for public policy. Nor do we address policy costs, either the monetary and political costs that must be expended to adopt the policy or the potential economic, social, or environment costs (or benefits) incurred as a side effect of the policy. Such costs must be weighed against the size of the VMT effect of a factor and any co-benefits in local government decision making. This analysis is beyond the scope of this paper.

We find sizable gaps in the knowledge base at a time when decision makers at the local level are being increasingly called upon to take action to reduce VMT. We summarize the empirical evidence on the effect of 14 distinct factors on VMT, organized into five categories:

LAND USE PLANNING

- residential density
- land use mix
- regional accessibility
- network connectivity
- jobs-housing balance

PRICING

- road pricing
- parking pricing

PUBLIC TRANSPORT

- public transport access
- public transport service

NON-MOTORIZED TRANSPORT

- pedestrian strategies
- bicycle strategies

INCENTIVES AND INFORMATION

- telecommuting
- employer-based trip reduction
- voluntary travel behavior change programs

This paper differs from previous reviews in the breadth of strategies for reducing VMT that it examines and in its focus on methodological quality, for example the reviews of the relationship between some of these factors and VMT (Graham-Rowe et al. 2011, Litman and

Steele 2011) and the meta-analysis of Ewing and Cervero (2010). This paper provides an assessment of the state of the evidence on the effectiveness of these strategies in reducing VMT rather than providing a definitive quantification of their effects.

CHALLENGES OF ESTIMATING THE EFFECT OF LOCAL ACTIONS ON VMT

Estimating the effect of local-level actions on VMT is difficult for three basic reasons: the relationship between these actions and VMT is often indirect, data on VMT is rarely collected in a way that facilitates estimating the effect of a particular action, and robust research designs are extremely difficult to implement in this area.

There are three basic strategies among the policies that aim to reduce VMT: reducing the need for travel, making alternatives to the private car more available and/or more attractive, and making cars less attractive to use for everyday trips (Handy 2006). Factors that are hypothesized to affect VMT include the land use characteristics that determine the distances between origins and destinations (e.g. density, network connectivity, land use mix, regional accessibility), the time and money costs of car use and of alternatives to the car, the availability of alternatives to the car , and information about how to reduce VMT. Each of the factors that this article reviews fit into one or more of these categories.

Some of these factors are directly affected by actions that can be taken by governments or companies, while others are not. For example, the road price factor is directly affected by road pricing policy. On the other hand, identifying a concrete policy action that will directly improve regional accessibility or land use mix is less straightforward. In these cases, there is an important question that the existing literature has not tackled: To what extent do local actions actually bring about changes in the factors that affect VMT? This article reviews only the work that aims to identify the relationship between factors and VMT; the evidence on the effect of policies on factors is substantially thinner.

In many of the cases where the factors are more directly affected by policy actions (e.g. road pricing and transit service), the literature focuses on the effect of the action on travel indicators that are not VMT (e.g. mode split or traffic volume). This is understandable, since these indicators are the direct target of these actions, and estimating the effect on VMT is more complicated. Although we do discuss some of the empirical findings regarding these alternative travel behavior indicators, our focus is to review studies that estimate the effect of changes in our 14 factors on VMT.

Data

Direct measurements of individual or household VMT are rarely used in research. The problem is not a technical one; VMT is not hard to measure. Virtually every vehicle on the road is equipped with an odometer that records VMT, usually with a high level of accuracy. The challenge is gaining access to the odometers and recording the readings. In some US states, odometer readings are recorded when vehicles are registered and/or inspected for safety and emissions.

Although odometer readings would provide some of the best measurements of VMT, there are other sources of VMT data. Most of the econometric studies reviewed in this article use individual trip distances derived from travel diary survey data as the source of daily VMT estimates. In these cases, the distances traveled are calculated for the reported trip origins and destinations along the road network using algorithms to identify the most likely route. Studies of particular programs – such as employer-based trip reduction – often collect their own data using a survey of program participants and sometimes a control group. The simulation studies included in this article use outputs for VMT from regional travel demand forecasting models, which are typically calibrated using a combination of travel diary survey data and Highway Performance Monitoring System traffic counts.

Research design

Most of the evidence on the impact of the 14 factors on VMT has obvious shortcomings, many of which are difficult to overcome. Here, we outline what is generally seen as necessary to answer this question, and use this as a benchmark to highlight how and why the existing research falls short. The best way to estimate the effect of an action on a particular behavioral outcome is usually seen to be to an experimental research design with the following basic structure:

- Measure the outcome of interest (in our case, VMT) for a random (or otherwise statistically appropriate) sample of the target population before the action is taken.

- Implement the action so that it affects only a portion of the sample: the experimental group. The portion of the sample that is not impacted by the policy will be the control group. Choose the experimental and control groups by random assignment, such that the two groups differ only due to chance variation.

- Measure the outcome of interest again for both the sample and control groups. Take this measurement at least once after the action is implemented. If the action is expected to have an immediate effect, one measurement will suffice. If the action's effect becomes apparent after a delay or time lag, however, a number of measurements over time will usually be necessary.

- Compare before-and-after measurements of the outcome of interest for the experimental and control groups to estimate the effect of the policy. As appropriate, control for differences between the experimental and control groups.

Existing research that aims to estimate the effect of local actions on VMT falls well short of this experimental ideal. True policy experiments are difficult to implement in the real world for both practical and political reasons. In many fields research often involves using natural experiments to study real world policy effectiveness. This approach has much promise in transportation research, but care must be taken because the experimental and control groups in a natural experiment may not fit the ideal of random assignment. In such cases, researchers could use further statistical methods to control for any systematic differences between the group affected by the policy and the group left unaffected. In cases where a true control group cannot be identified, quasi-experimental matching techniques can be used to identify synthetic control groups that are intended to be as similar as possible to an experimental group. For transportation applications, see, e.g., Funderburg et al. (2010).

Table A-1 identifies some challenges faced when they try to estimate the effect on VMT of the factors we review in this article, and indicates which specific research challenges are commonly associated with which factors. It is these challenges – inherent in the relationships between VMT and these factors – that often make any sort of experiment-based method unworkable.

The VMT effects of changes in some factors can only be seen over a long time period, either because the factor itself changes slowly or because there is a delay in the effect of the changed factor on VMT. When effects occur over a long period, many other variables that affect VMT are also likely to change, making it difficult to separate the VMT effect of the factor of interest from the effect of everything else. The land use planning factors all fall into this slow-changing category. In terms of obtaining a clean estimate of their effect on VMT, this presents a challenge. However, as policy options, they have the advantage that they are likely to be long-lasting – what takes a long time to do also takes a long time to undo.

For many factors, it is difficult to test the effect because it is hard to identify the treatment group, the control group, or both. Many of the actions that aim to influence VMT do so by making non-car modes more attractive (e.g. public transport enhancements, bicycle and pedestrian strategies). These can be implemented for part of a network, leaving the remainder of the network as a control of sorts. However, even these policy experiments would not be true randomized trials due to the spatial nature of transport networks and the spatial clustering of types of people in cities.

Even road and parking pricing are difficult to evaluate using an experimental design, mainly because it is hard to identify the treatment group. A proper experimental design to evaluate the effect of a road or parking pricing policy would randomly assign potential users of the facility to be "payers" - ideally at a variety of fee levels - or "non-payers", observing their VMT choices both before and after implementation of the pricing policy experiment. Aside from the practical difficulties of identifying the population of a facility's potential users and measuring their VMT, random assignment of fee payment is not likely to be politically acceptable.

For many of the factors we look at, work studies use different variables to represent the same thing – often because there is not an agreed-upon measure that represents the factor. This makes it difficult to directly compare study results, even when studies are looking at the same factor. For instance, network connectivity has been represented by intersection density, percent of intersections that are not dead ends, and number of four-way intersections within a certain distance of home. There has been limited work done to determine which of the variables best represents each of the factors.

For any factor that affects a particular location, residential self-selection presents a research challenge. When individuals relocate to be near, for instance, transit stations or bicycle paths, or to be in areas with better job access, these people are self-selecting to be, in effect, in the treatment group for these factors.

Table A-1: Common research challenges by factor for estimating effect on VMT

FACTOR	Factor changes slowly	Delay in effect on VMT	Hard to identify treatment group	Hard to identify control group	Multiple variables represent factor	Residential self-selection a concern	Other self-selection
LAND USE PLANNING							
Residential Density	X	X	X	X	X	X	
Land Use Mix	X	X	X	X	X	X	
Regional Accessibility	X	X	X	X	X	X	
Jobs-Housing Balance	X	X	X	X		X	
Network Connectivity	X		X	X	X	X	
PRICING							
Road Pricing			X				
Parking Pricing			X				
PUBLIC TRANSPORT							
Distance to Transit						X	
Transit Service					X	X	
NON-MOTORIZED TRANSPORT							
Pedestrian Improvements		X			X	X	
Bicycling Improvements		X			X	X	
INCENTIVES AND INFORMATION							
Employer-Based Trip Reduction							X
Telecommuting							X
Voluntary Travel Behavior Change							X

The factors that can be easily evaluated using a quasi-experimental design are employer-based trip reduction, telecommuting, and voluntary travel behavior change programs. For these factors, the main issue that arises is that those who participate self-select into the programs. This means that the results - while quite robust as estimates of these programs' effect on VMT of participants - are not necessarily generalizable to the whole community of interest.

Criteria to help identify the best evidence from the empirical literature

We used six criteria to separate the best evidence from the rest of the empirical work in this area. We are aware of no existing studies that satisfy all of these criteria, but all of the studies that we highlight in the next section satisfy at least one of them. Here, we identify and describe each of these criteria in turn.

Use disaggregate data: Some studies, mostly from the 1990s, use data aggregated to geographic areas, such as census tracts or transportation analysis zones. In those studies, the unit of observation is the geographic area, not an individual traveler or household. Using aggregate data obscures behavioral impacts at the household level and reduces the ability to control for sociodemographic characteristics. This makes it difficult to link results to behavioral theories of travel, and therefore difficult to use these studies to make inferences about causality. The results of studies based on aggregate data can also be misleading because it is not correct to apply these results to individuals due to the possibility of ecological fallacy – that correlations observed at the aggregate level may not hold for individuals. It is for these reasons that studies based on disaggregate data – at the level of the individual, household, or firm – are preferable. Nearly every study included in this review is based on disaggregate data.

Where applicable, control for residential self-selection: As discussed in the previous section, residential self-selection refers to the possibility that people might choose where to live based in part on how they wish to travel. If this is true, then it is a foregone conclusion that, for instance, people who live near transit will have higher rates of transit use (and relatively low VMT) and people who live in walkable neighborhoods will choose to walk for many of their trips (and relatively low VMT). Studies that estimate these correlations without controlling for the self-selection effect may be mistakenly interpreting their results to mean that if planners change the built environment, then people will drive less. Some studies – including many that we review in this article – attempt to control for self-selection using a variety of methods (see Cao et al. 2009 for a comprehensive review and critique of these methods). Table 1 identifies those factors for which residential self-selection is a concern.

Employ a before/after research design: A research design that compares VMT data from before and after a particular factor is changed is the best way to ascertain that the change in the factor caused the change in VMT. This is impossible when data collection begins after the relevant factor changes. In some cases, a set of recall survey questions about people's travel choices before the factor changed can be used as a substitute. In many cases, however, only cross-sectional data are available, making it hard to be sure whether the identified effect is due to differences in the factor of interest, or other differences between observations in the dataset. Unfortunately, evaluation of the impact of local actions – if it is conducted at all – is often not begun until after the action has been taken and the associated factor has changed.

Where possible, use a control group: Estimates of the effect on VMT of some factors can benefit from comparing data collected from both a treatment group and a control group that did not experience any change in the factor of interest. Similar to a before/after research design, use of a control group makes causality results more robust. Table 1 identifies those factors for which it is hard to identify control groups.

Directly estimate factor effect on VMT: The bulk of the existing evidence on the relationship between factors and travel behavior focuses on travel behavior measures other than VMT. Variants of mode choice models are particularly common. Although these related measures do provide an indication of the likely direction of the factor's impact on VMT, direct estimates of the VMT effect size are best. Every study listed in Table 2 provides direct estimates of the factor's effect on VMT.

Properly report elasticities and/or marginal effects: Many studies that report the results of multivariate statistical models examining VMT do not report elasticities or marginal effects. In fact, the researchers who wrote one of the existing surveys of the evidence on the relationship between land use variables and VMT were forced to calculate their own elasticity estimates from the available information in many of the papers they review (Ewing and Cervero, 2010). Additionally, most regression studies of VMT use non-linear specifications. In such cases, the marginal effect and the elasticity should be calculated for every observation in the data set, and reported effects should be averages of these individual effects. Usually studies that report elasticities report them evaluated at the sample mean – an approach that is appropriate for linear regressions but incorrect for non-linear specifications (Brownstone, 2008).

We should also note that because the policy briefs were prepared for the California Air Resources Board, priority was given first to studies from California, then from elsewhere in the U.S. For factors for which studies meeting the six criteria were difficult to find, international studies were sometimes included. The goal in preparing the policy briefs was to identify the best evidence for California communities rather than to complete a comprehensive review of the international work. The focus on California studies helps to control for numerous contextual variables, such as weather and culture, which might influence the size of the effects of the fourteen factors. Thus we might expect that this review produces a narrower range of effect sizes than would be found in an international review.

HOW MUCH DO LOCAL ACTIONS AFFECT VMT? THE EVIDENCE

There is evidence that local actions can affect VMT substantially by changing the policy-sensitive factors we highlight in this article. Table A-2 summarizes estimates from the best studies we found, according to the above criteria, of the effect size for of each of these factors on VMT, and provides basic information about the variable used to represent each factor in each study. Because empirical data and methods differ by factor and because the size of the literature varies by factor, study sophistication and quality are not at the same level for all of the fourteen factors. Where the effect size is given in Table A-2 as a unit-less number, it is the elasticity of VMT with respect to the factor, measured as listed. Where the effect size is given as a percent, it is the effect of the listed change in the factor.

The following subsections discuss the evidence for each category of factors in turn. For some factors, we discuss evidence on the effect of the factor on variables such as mode split and traffic volume in the text below – especially when VMT results are lacking in the literature. The results summarized in Table A-2, however, are restricted to those that report an effect on VMT as the outcome variable.

Overall, it is clear from the literature that there are factors that can be changed by local-level actions that are likely to reduce VMT. Land use factors have been studied the most, and the estimated effect sizes of individual factors tend to be relatively small. Robust evidence on the effect sizes of multiple land use factors together is slim. However, since there are a variety of reasons – besides VMT reduction – that localities might want to alter land use patterns, it may make sense to implement policies to change land use despite their relatively small impact on VMT.

Policies targeting VMT more directly (i.e. telecommuting, employer-based trip reduction, and voluntary travel behavior change programs) report large effect sizes, but most of these estimates apply only to those individuals who voluntarily opt into the programs. Information on the determinants of the proportion of people opting into these programs is needed to accurately gauge effect size. To our knowledge, this remains a gap in the literature.

Estimates of the effect on VMT of both pricing strategies and strategies that make alternatives to the auto more attractive (transit and non-motorized transport) are generally lacking. In our estimation, these areas represent the largest gap in the literature. Again, however, there are reasons other than VMT reduction to implement these strategies.

Table A-2: Estimated effect of VMT with respect to policy-sensitive factors in studies reviewed

Factor	Study Citation	Effect Size	Variable
LAND USE PLANNING			
Density	Bento et al. (2005)	≤ -0.07	residential density
	Brownstone and Golob (2009)	-0.12	residential density
	Fang (2008)	-0.08 to -0.09	residential density
	Heres-Del-Valle and Niemeier (2011)	-0.19	residential density
Land Use Mix	Chapman and Frank (2004)	-0.04	entropy measure
	Ewing and Cervero (2010)	-0.09	entropy measure
	Frank et al. (2005)	-0.02	entropy measure
	Kockelman (1997)	-0.10	entropy measure, land use dissimilarity
Regional Accessibility	Bento et al. (2003, 2005)	-0.18	population centrality measure
	Cervero and Kockelman (1997)	-0.25	accessibility to jobs using gravity measure
	Ewing and Cervero (2010)	-0.20 -0.05 -0.22	1. job access by auto 2. job access by transit 3. distance to CBD
	Kuzmyak (2006)	-0.13	accessibility to jobs using gravity measure
	Zegras (2010)	-0.23	distance to CBD
Jobs-Housing Balance	Bento et al. (2003, 2005)	-0.06	metropolitan-level balance

Factor	Study Citation	Effect Size	Variable
	Cervero and Duncan (2006)	1.-0.299[g] 2.-0.329[g]	1. jobs within 4 miles of home 2. jobs in the same occupational category within 4 miles of home
	Kockelman (1997)	-0.31	jobs within a 30 minute radius of home by car
Network Connectivity	Bento et al. (2003, 2005)	-0.07	road density (lane-miles per square mile)
	Cervero and Kockelman (1997)	1. No effect 2. -0.59 3. 0.18 4. 0.46	1. 4-way intersections HH VMT, all purposes 2. 4-way intersections HH VMT, non-work 3. quadrilateral blocks HH VMT, all purposes 4. quadrilateral blocks HH VMT, non-work
	Ewing and Cervero (2010)	1. -0.12 2. -0.12	1. intersection or street density 2. percent 4-way intersections
	Chapman and Frank (2004)	-0.08	intersection density near home
	Boarnet et al. (2004)	1. -0.06[a] 2. -0.19[a]	1. 4-way intersection density near home 2. total intersection density near home
	Fan and Khattak (2008)	-0.26	percent of road ends that are intersections rather than dead ends
PRICING			
Road Pricing	Rufolo and Kimpel (2008)	1. -11% 2. -14.6%	1. 1.2 cents per mile 2. 10 cents per mile in Portland during peak hours, 0.43 cents per mile otherwise
	Deakin et al. (1996)	-0.2 to -0.25	total cost of driving in Bay Area and Los Angeles
	Rodier (2002)	-10%	5 cent per mile in Sacramento
	Safirova et al. (2007)	-14.5%	10 cent per mile in Washington D.C.
Parking Pricing	Shoup (1997)	-12%[b]	parking cash out
	Deakin et al. (1996)	-2.3% to -2.9%	$3 per day workplace parking price in 1991 (~60% of hourly value of commuter travel time)
	Dueker et al. (1998)	-1.9%	$3 per day workplace parking price
	Lautso et al. (2004)	-2.8%	60% of hourly value of commuter travel time
PUBLIC TRANSPORT			
Distance to Transit	Bento et al. (2003)	-0.08	instrumented distance to any transit stop

Factor	Study Citation	Effect Size	Variable
	Ewing and Cervero (2010)	-2.5%	one mile closer to any transit stop
	Pushkar et al. (2000)	-1.3%	move from two miles to one mile away from any transit stop
	Bailey et al. (2008)	1. -5.8% 2. -2.0%	1. One mile closer to rail station, within 2.5 miles of rail 2. ¼ mile closer to bus stop, within ¾ mile of stop
Transit Service	no effect on VMT estimated		
NON-MOTORIZED TRANSPORT			
Pedestrian Improvements	Cervero and Kockelman (1997)	no effect	sidewalk width
	Fan (2007)	-0.02	sidewalk length
	Parsons Brinckerhoff Quade Douglas (1993)	-0.19	Pedestrian Environment Factor
Bicycling Improvements	no effect on VMT estimated		
INCENTIVES AND INFORMATION			
Employer-Based Trip Reduction (EBTR)	Herzog et al. (2006)	-4.16%[b] to -4.79%[b]	voluntary employer-based commute trip reduction programs around the US
	CTR Task Force 2005 Report	1. -1.6% 2. -5.9%[b]	WA state commute trip reduction program
	Hillsman et al. (2001)	-1.33%	WA state commute trip reduction program
	Lagerberg (1997)	-6%[b]	WA state commute trip reduction program
Telecommuting[d]	Kitamura et al. (1991)	1. -76.6%[e] 2. -48.1%[f]	home-based telecommuting
	Henderson and Mokhtarian (1996)	1. -90.3%[g] 2. -66.5%[e] 3. -62.0%[g] 4. -53.7%[e]	1-2. home-based telecommuting 3-4. center-based telecommuting
	Balepur et al. (1996)	1. -77.2%[g] 2. -64.8%[e]	center-based telecommuting
Voluntary Travel Behavior Change (VTBC)	Sloman et al. (2010)	-5% to -7%	5-year sustained comprehensive VTBC campaign in 3 English cities (Smarter Choices)
	Socialdata America (2007)	-9%[c]	Individual marketing program to reduce single-occupant vehicle use in 3 Oregon cities
	Fujii and Taniguchi (2005)	-12%[c]	average reduction for participants in travel feedback programs in 5 Japanese cities

[a] These elasticities are those for non-work VMT only.

[b] This is a VMT reduction estimate only for the commute trips of affected workers.
[c] This is a VMT reduction estimate only for program participants.
[d] These are VMT reduction estimates for program participants on the telecommuting day only.
[e] This is a VMT reduction estimate for all personal VMT.
[f] This is a VMT reduction estimate for household VMT.
[g] This is a VMT reduction estimate for commute VMT only.

Land use planning

Here we review the empirical evidence for the relationship between VMT and residential density, the mix of land uses, regional accessibility and jobs-housing balance, and road network connectivity within a neighborhood. Land use planning studies are largely cross sectional and based on metropolitan, state, or national travel diaries. The behavioral link between land use and VMT is that these factors directly affect the distances people travel to access common destinations such as jobs, shopping, schools, and parks. If people can access destinations by traveling shorter distances, then VMT will go down. At the neighborhood scale, we expect that dense neighborhoods with good street network connectivity and a diversity of uses in close proximity to housing result in fewer vehicle miles traveled. At the sub-regional scale, we expect that areas with a better balance between housing and jobs will have lower VMT because commutes will be shorter. At the regional scale, we expect that distances to jobs and other major destinations will affect VMT.

The single land use variable that has most often been studied in the literature is residential density, largely because density data is readily available. Density is correlated with many of the other factors that we expect to affect VMT, including both land use factors and factors such as transit service and parking prices. Many researchers have pointed out that the observed effect of density on travel may actually be mainly due to the effects of these other factors (e.g. Chatman 2008, Salon 2009). Table A-2 lists the results of four of the best existing empirical studies that estimate the effect of density on VMT, and all but Fang (2008) at least partially control for residential self-selection. Bento et al. (2005) use national data from 1990, while the other three studies use 2001 data from California, and each study uses a distinct estimation methodology. These differences may help to explain the range of results.

The studies examining density that we include in this review are held to a high standard of methodological rigor. However, work on land use factors beyond density that impact VMT is substantially sparser. While for these factors we also selected only studies that are based on disaggregate data, we have included many studies in these categories of Table A-2 that do not control for residential self-selection.

Looking at land use mix, we see that measures of the variety of land uses that appear in a neighborhood are estimated to have a relatively small effect on VMT, with elasticities of -0.1 or less. Although these studies all control for many other factors that could affect VMT, none of them control for residential self-selection.

Network connectivity, usually represented as road density or as an intersection-based measure, has been estimated to have a slightly larger impact on VMT – though the range of estimated elasticities is large. The bulk of the elasticities reported for VMT with respect to network connectivity in Table A-2 are between -0.06 and -0.26. Again, all of these studies controlled for other factors that could affect VMT, but only Fan and Khattak (2008) adjusted for residential self-selection, and their estimated elasticity is at the high end of this range. One possible explanation for the variation in these results is that each study uses a different measure of connectivity.

One clear insight that seems to be emerging is the importance of regional accessibility to jobs and jobs-housing balance. For regional accessibility, elasticities in five studies summarized in Table A-2 are between -0.13 and -0.25, with more evidence at the higher end of the range. Estimated elasticities of VMT with respect to jobs-housing balance are more variable, but the evidence from studies examining neighborhood-level balance estimate elasticities between -0.29 and -0.35. The effect of employment accessibility on VMT appears to be related to the large contribution of longer trips to VMT. For example, Boarnet, Houston, et al. (2011) found from travel diary data that nearly 55% of VMT in the Los Angeles region could be attributed to trips of 20 miles or more. A nearly identical proportion was found for the nationwide 2001 NHTS sample.

These results suggest that regional employment accessibility may provide a leverage point for localities aiming to curb local transport-related greenhouse gas emissions. However, the link between specific policies and improving employment access is unclear. Policies that cluster employment closer to residents (decentralizing jobs), that cluster residents closer to employment (favoring infill residential development), or that reduce travel times between centers of housing and jobs (investing in transportation infrastructure) will all improve accessibility. Which of these will be most effective will likely depend on characteristics of the existing land use-transportation system in a city, and the literature reviewed here does not provide guidance that helps local decision makers choose between them.

Bento et al. (2005) provide some insight into the potential of land use policy packages, finding that the combined effects of numerous factors can be substantial. Bento et al. (2005) compared predicted VMT for people with the same socioeconomic characteristics living in Atlanta and Boston to get insight into the effect of changing multiple land use variables in ways that reflect the different urban form in those two cities. Bento et al. (2005) find that predicted VMT in Boston is 25% lower than in Atlanta, suggesting that the combined effect of changing multiple land use variables will be larger than the effect of changing density alone.

There is reason to believe that the impact of land use on travel is characterized by thresholds, and that therefore single elasticity estimates are unlikely to be accurate for all or even most of the distribution of land use factor values. Boarnet, Joh, et al. (2011) provide evidence that within small neighborhoods (a mile or less from end to end) residents can have as much as a fivefold difference in walking trip generation rates and differences as large as 30% in car trip generation rates. In different research, Boarnet, et al. (2011) found that the elasticity of VMT with respect to employment accessibility ranged from statistically insignificant to greater than one in absolute value across quintiles of employment accessibility in the Los Angeles region. Similarly, Salon (2009) shows that elasticities of commute mode share with respect to population density are significantly different between the boroughs in New York City. All the studies summarized in

Table A-2 report a single average VMT effect of each factor for large geographical areas. More work is needed to gain a better understanding of the variation in effect size across space.

Road and parking pricing

One of the main factors that we expect to affect VMT is the cost of car use, and pricing strategies are repeatedly suggested by transport planners and economists as a way to reduce the negative externalities of driving. The behavioral mechanism at work is simple: as the cost of driving goes up, we expect that people will use cars less, directly leading to reduced VMT. Road and parking prices are the two major portions of this cost that are affected by local actions. Although fuel prices are also a large portion of the cost of driving, we do not review the evidence on the effect of fuel price changes on VMT because fuel prices are not influenced by local actions.

Surprisingly, the bulk of the literature on road and parking pricing does not examine VMT. For that reason, the evidence reported in Table A-2 on metropolitan-scale VMT impacts from pricing is largely from simulation models. This is true despite the existence of a well-developed empirical literature that examines traffic and other demand measures as a function of road and parking prices. This is a large gap in the existing empirical literature, especially since pricing is expected to be one of the most effective actions that can be taken to reduce VMT.

There are four types of road pricing :

- link or point tolling-where users pay for access to a roadway segment such as a toll road or bridge,
- cordon pricing-where drivers are charged when crossing the boundary of a predefined tolling area (typically a downtown or central business district), and
- distance charging-where users pay according to distance driven on the road network.
- time charging whereby road users are charged for the time spent on a road

The first two types of road pricing have been implemented on many road segments and in a variety of cities, but to our knowledge, no distance charging programs currently exist. Unfortunately we do not have evidence on the impact of link tolling and cordon pricing on VMT. For link tolling, studies show that the elasticity of traffic volume with respect to price is in a range from -0.1 and -0.45 (e.g. Goodwin 1989, Harvey 1994, and Burris et al. 2001). Variations within that elasticity range can be attributed to local conditions such as the existence of nearby non-tolled alternative routes, the availability of alternative travel modes, the predominant trip purpose on the link, and congestion levels on alternate routes. Traffic reductions of between 12% and 22% have been achieved through cordon pricing in five major European cities (CURACAO 2009, Eliasson 2009). In Singapore, where cordon charging has been in place since the 1970s, traffic volume is estimated to decrease by 2 to 3% for every 10% increase in the cordon charge (Olszewski 2007).

It is important to note that reductions in link volume or traffic counts at a cordon may not translate into similar reductions in overall metropolitan area VMT due to spillover effects (i.e. road price increases on particular links encourage the choice of alternate routes or destinations).

Leape (2006) reports that after London implemented a cordon toll, about one quarter of the reduction in trips through the charging zone actually diverted outside of the zone, but congestion outside of the zone hardly increased, possibly due to coincident implementation of traffic management programs (e.g. improved traffic signal timing) outside of the charging zone. Most studies of link tolling and cordon counts use before/after longitudinal designs, and so are well positioned to identify the causal impact of price changes on traffic volume, if not overall metropolitan area VMT.

Because no operational distance charging programs currently exist, we present results from travel model simulation studies and from a distance charging experiment that was conducted in Oregon. Deakin et al. (1996) reported a simulated price elasticity of VMT of between -0.2 and -0.25 based on models of the San Francisco and Los Angeles metropolitan areas. Rodier (2002) found that a simulated 5 cent per mile VMT charge in the Sacramento area would result in a 10% VMT reduction. Safirova et al. (2007) found that a simulated 10 cent per mile VMT charge in the Washington DC area would result in a 14.5% drop in VMT. The Oregon pilot program yielded similar-sized VMT reductions from an experimental distance charging scheme that replaced the gas tax and therefore was designed to be revenue neutral (Rufolo and Kimpel 2008). Though based on a small experiment that did not employ a randomized trial methodology, these results are surprising and notable. They suggest that travelers might be especially responsive to VMT charges, even when a policy is designed specifically so that the variable cost of driving does not change for the average traveler.

Turning to parking pricing, we again encounter the problem that VMT effects are not commonly reported for studies based on empirical data. The single exception to this that we found was a study of eight employer parking cash-out programs, reporting that those employees who accepted the parking cash-out reduced their VMT by 12% (Shoup 1997). The simulation-based evidence suggests that metropolitan VMT would decrease by approximately 2-3% in response to daily parking prices equal to 60% of hourly commute time cost (Deakin et al. 1996, Dueker 1998, Lautso et al. 2004).

Public transportation

In general, the literature focuses on four broad measures of transit access and service: (1) fares, (2) service frequency, (3) service miles or hours, and (4) distance to the nearest transit station. The behavioral link from these factors to VMT is that as transit becomes cheaper and/or more convenient for travelers to use, they will substitute transit trips for vehicle trips, thereby reducing VMT.

For fare, frequency, and service miles/hours, the literature provides evidence on the relationship of these characteristics of a transit system to transit ridership, but the effect on VMT is not quantified. Results from the literature estimate elasticities for transit ridership of 0.5 for increases in service frequency, 0.7 for increases in service miles or service hours, and -0.4 for increases in fares. Paulley et al. (2006) is one of the few studies that examined links from service characteristics to car use, and they found that the elasticity of automobile mode share with respect to bus transit fare was about -0.05, approximately one-tenth the fare elasticity estimate of transit ridership. We expect that as transit ridership increases, VMT will decrease, but the effect is likely to be less than one-to-one, both because new transit trips do not always replace car trips and because of latent demand for road space (see Duranton and Turner 2011).

For distance from transit, effect sizes in the literature range from a 1.3 to an 8% decrease in VMT per mile from a station (see Table A-2). However, the implied gradient for VMT likely occurs only within a relatively small radius around stations. The effect of proximity to any particular transit station will depend on factors such as transit level of service and destinations served by the transit line(s), but only one of the studies (Bento et al. 2003) partially controls for these service factors by combining transit proximity with actual average transit usage data.

Most of the studies of transit service (fare, frequency, service miles/hours) use longitudinal data, but several do not include covariates to control for other aspects of the land use/transport system that may have changed over time. For distance from transit stations, the literature uses methods more similar to studies of land use factors – complex statistical models of cross-sectional data, rather than longitudinal research designs. Residential selection could account for part of the effect if transit riders choose to live closer to transit stations, but only two of the studies reported in Table A-2 accounted for self-selection (Bento et al. 2003 and Bailey et al. 2008).

Looking forward, there is little evidence that links recent innovations such as bus rapid transit (BRT) to VMT, and the literature on distance to transit and service characteristics tends to predate much of the implementation of BRT systems. In addition to that gap in the literature, there is little evidence on the VMT or transit ridership effect of actions such as transit marketing and information campaigns.

Non-motorized transportation

Non-motorized transport includes walking, bicycling, and a variety of other human-powered transport modes (e.g. cycle-rickshaws, skateboards, rollerblades, ice skates, x-country skis). As non-motorized modes become more convenient and safe, more people may substitute these modes for automobile travel, leading to reduced VMT. Although non-motorized trips are typically rather short, there is evidence that they often substitute for longer vehicle trips, and therefore may have a larger impact on VMT than the non-motorized trip length would suggest (Guo and Gandavarapu 2010).

The literature on non-motorized transport has focused mainly on the impact of pedestrian and bicycle infrastructure and educational programs on the amount of walking and bicycling that people engage in – not on the VMT impact. Most studies give an elasticity of walking with respect to sidewalk coverage or length in the range of 0.09 to 0.27 (e.g. Cervero and Kockelman 1997, Fan 2007, Ewing et al. 2009). For bicycling, Dill and Carr (2003) estimated using aggregate data that the elasticity of bicycle commuter mode share with respect to either bike lane density or state per capita bicycle spending is 0.32. In most communities, however, walking and biking represent a small share of travel, so even relatively large percentage changes in walking and/or bicycling mode share may lead to only small reductions in driving.

There have been a handful of studies that identify the VMT effect of walking, and the results have been mixed. In a study of Portland, Oregon, Parsons Brinkerhoff (1993) found an elasticity of VMT with respect to a measure of pedestrian quality of -0.19. Other studies, however, found little or no association between the pedestrian environment and VMT or driving (Cervero and Kockelman 1997, Fan 2007). Kitamura, et al. (1997) found that the presence of sidewalks in the neighborhood was associated with a 0.14% decrease in vehicle trips. Guo and Gandavarapu (2010) found that each mile of roadway with sidewalks within 1 mile of a person's home decreases VMT by 0.645 miles. To our knowledge, the link between increased bicycling and VMT reduction has not been empirically quantified. Noland and Kunreuther (1995) did estimate an elasticity of car mode share with respect to bicycle parking availability (-0.01) and with respect to bicycle convenience (-0.02).

Most of the existing empirical studies of walking and bicycling are based on cross-sectional data, and so inferring causality is difficult. Only recently have studies included controls for residential selection when examining non-motorized travel (e.g. Boarnet et al. 2008, Frank et al. 2007, Handy and Xing 2011, Handy et al.; 2006 2010).

Because of the relatively shorter distances of bicycling and, especially, walking trips, non-motorized policies have a tight spatial focus. For this reason, it is particularly important to develop studies that are sensitive to local settings and that can measure variations in effect sizes across different geographies and population groups. That will often require collecting specialized data, as regional travel surveys will usually not have sufficient spatial focus or sufficiently large numbers of observations of non-motorized trips to identify the effect of non-motorized programs. The non-motorized literature has already made strides in pioneering the use of specialized, often electronic, data collection (e.g. Rodriguez et al. 2005).

Incentives and information

In the final category of local factors that can reduce VMT are telecommuting, employer-based trip reduction (EBTR) programs, and voluntary travel behavior change (VTBC) programs. The behavioral mechanism for each of these is direct, since they are all directly aiming to reduce VMT through promoting changes in people's travel choices. The VMT effects of these factors tend to be quite large (see Table A-2), but most of these effect size estimates are calculated only for those people who voluntarily opt into the program (except for Hillsman et al. 2001 and Sloman et al. 2010, who estimate citywide effect sizes).

Telecommuting studies have typically measured changes in VMT for telecommuters on telecommuting days. The effect of telecommuting in a region depends on the reduction in VMT per telecommuting day, the number of days of telecommuting per worker, and the number of workers telecommuting in the region. The results reported in Table A-2 apply only to the first of these, and are therefore insufficient to fully evaluate the effect of telecommuting on regional VMT. With that caveat, the estimated effect sizes are large, ranging from a 53.4 to a 76.5% reduction in personal VMT on telecommuting days.

EBTR programs include a wide variety of elements including employer-provided alternative mode services, carsharing programs, guaranteed ride home for transit users, and financial incentives to encourage alternatives to single-occupant car commuting. Most studies examine state-mandated EBTR programs, which have applied to large firms in major cities. Effect sizes for the reduction in commute VMT for participating firms are estimated to be between 4 and 6%. Looking at region-wide VMT effects, estimates are in the vicinity of a 1% reduction.

VTBC programs can be characterized into two categories – public education campaigns that target a whole population and travel feedback programs that target a small set of households or workplaces. Travel feedback programs employ a more hands-on approach to help individuals and groups rethink their travel choices in light of improved information about their transportation options. Overall, the evidence collected from VTBC evaluations indicates that VMT reductions of 5 to 8% are achievable among participants. The results of the extensive five-year English VTBC program evaluated by Sloman et al. (2010) appear to indicate that city-wide VMT reductions of 5 to 7% are achievable, at least in areas where alternatives to private car use exist.

Although these factors all have the issue that participants self-select into the treatment group, the literature in this area has at least two methodological strengths. First, because there is usually an easily identifiable point in time when the programs were implemented, researchers have been able to use before/after research designs. Second, many, although not all, studies have included measurements from control groups.

OPPORTUNITIES FOR FUTURE WORK

This paper has reviewed existing literature that explores the relationship between VMT and factors that can be influenced by policies and programs in the areas of land use planning, road and parking pricing, public transport, non-motorized transport, and incentives and information. While individual studies differ as to exact effect sizes, it is clear that changes in many of these factors do affect VMT. That said, relatively large gaps in this evidence base remain. Here, we highlight what we view as the five most important of these gaps for informing policy, and suggest how researchers might begin to fill them.

First, we expect that the effect sizes for many of the factors reviewed would vary across space and people. However, the lion's share of the existing analysis reports only average effect sizes for large geographies and across diverse populations. The small amount of research that has looked at how effect sizes vary according to specific context suggests that the association between land use characteristics and VMT can vary substantially. Because policy application requires an understanding of whether and where the application of different policies would be most effective in affecting VMT, this gap presents an important opportunity for future work.

Second, we expect that the effect of local actions on VMT will depend somewhat on which other local actions are taken simultaneously. In the real world, multiple related policies and programs are often implemented at the same time – whether they are purposely coordinated or not. However, the existing literature provides scant guidance on policy interaction effects. More research that focuses on how these actions interact could provide key information to help decision makers craft more effective policy packages.

Third, many of the studies reviewed here rely on cross-sectional data to estimate effect sizes. This compromises causal inference, leaving open questions of whether the estimated effect size can be trusted as the basis for policy action. Going forward, there is an opportunity to greatly improve our understanding of causality by using experimental research designs – studying current policy "natural" experiments with before-after data collection and carefully selected control groups.

Fourth, there is an opportunity to improve the data sources used to measure VMT. Most existing studies use measures of VMT derived either from national or regional travel diary surveys or from special surveys associated with program evaluations. Traditional travel diaries are expensive to conduct and therefore occur infrequently and give only sparse coverage of small geographic areas. Technology has advanced to the point where there are many opportunities for specialized travel data collection. Geographic positioning systems allow detailed tracking of travel, and have already been applied in some transportation studies (e.g. Bricka et al. 2009, Rodriguez et al. 2005). Using more traditional survey methods, researchers have collected specialized travel data to evaluate specific land use characteristics in small study neighborhoods (e.g. Krizek and Johnson 2006 or Handy et al. 2006). Building on those and similar efforts, development of standardized, relatively low-cost methods to collect travel data to support before-after program evaluations would be an important contribution to the state of the practice.

Finally, the link is sometimes indirect between policies and the factors in the literature that have been shown to affect VMT. This is particularly true for land use factors, and results in the available evidence on effect size being less useful for decision makers than it could be.

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