Income, Location Efficiency, and VMT: Affordable Housing as a Climate Strategy

by

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Introduction

Planning policies aimed at reducing vehicle-miles traveled (VMT) combined with growing consumer demand for walkable, transit-rich neighborhoods have led to increased development interest in location-efficient neighborhoods – i.e., those places associated with the lowest transportation costs. Location-efficient places are characterized by high levels of accessibility to jobs and services that enable residents to drive less either by making shorter trips or by shifting trips to transit, walking, and bicycling. This increased development interest, typically focused on residences for higher-income populations, but in neighborhoods historically home to lower-income populations, has raised questions about the best use of the scarce, location-efficient space for achieving VMT reduction goals. Specifically, does developing a location-efficient space as affordable housing yield more VMT reductions than as market-rate housing?

Answering this question is of immediate relevance to the state of California, which committed itself to reducing its greenhouse gas (GHG) emissions to 1990 levels by 2020 through, among other approaches, a market-based GHG emission Cap-and-Trade Program (*Global Warming Solutions Act*, 2006) and a commitment to "improved land use and transportation policy" to increase location efficiency (*Sustainable Communities and Climate Protection Act*, 2008). In the summer of 2014, after the Cap-and-Trade program began yielding substantial revenues, the state passed a budget to allocate auction proceeds among relevant programs (*Budget Act*, 2014) and included a 20% minimum allocation to the newly-formed Affordable Housing and Sustainable Communities (AHSC) program. The state awarded an estimated $120 million to AHSC in the first fiscal year (2014-1015) alone and is expected to award $400 million in the second fiscal year up to an anticipated $500 million annual award by the end of the decade – at least half of which must support affordable housing in transit-accessible places (State of California, 2014).

The California case is important as the state represents the leading edge of both climate change and VMT-reduction policies in the United States. This research, therefore, addresses the issue of affordable housing as a climate strategy in the context of California. This work first estimates an econometric model for predicting household VMT; explicates that model to understand the theoretical relationships between income, location efficiency, and VMT; applies that model to statistically representative households living in and out of location-efficient areas in California; and identifies the implications of these analyses for revising the AHSC policy.

While the predictive model finds that that lower income households drive less and that households living in more location-efficient locations also drive less, this research finds that location-efficient affordable housing is a justified climate strategy not because location-efficient living is associated with deeper absolute VMT reductions for lower-income populations than for wealthier populations – no statistically significant differences were found – but because lower-income populations use location-efficient space more efficiently, which allows the same land area to yield more VMT reductions.

Literature Review

Descriptive analyses of travel surveys have repeatedly demonstrated that low-income households drive fewer miles than other households – one analysis of the 1995 National Personal Transportation Survey found low-income households drove half the annual miles of non-low-income households (Murakami & Young, 1997). However, since income is often correlated with other factors, such as household composition and location efficiency, descriptive studies cannot tease out these relationships (e.g. Pucher & Renne, 2003).

Fortunately, many econometric studies on location efficiency and VMT have included income as a controlling variable (Cervero & Kockelman, 1997; Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002; Boarnet, Houston, Ferguson, & Spears, 2011; Salon, 2013; Giuliano & Dargay, 2006; Bento, Cropper, Mobarak, & Vinha, 2005; Srinivasan & Rogers, 2005; Khattak & Rodriguez, 2005; P. Haas, Morse, Becker, Young, & Esling, 2013; P. M. Haas, Makarewicz, Benedict, & Bernstein, 2008). These studies have represented income as linear (Cervero & Kockelman, 1997), step (Boarnet et al., 2011), combined linear and quadratic (Salon, 2013), combined linear and exponential (Holtzclaw et al., 2002), and logarithmic (Bento et al., 2005) functions. Aside from the one linear formulation (Cervero & Kockelman, 1997) which was not significant within the final model, these studies all find VMT rising quickly for low income levels then growing more slowly, or even declining (Holtzclaw et al., 2002), at higher income levels. For example, Boarnet et al. (2011) find VMT rises steeply with income until households earn $50,000 a year, roughly the median income of the study area, but then stagnates until households earn more than $150,000, at which point it rises again slightly.

No econometric study using data disaggregated at a household level identified income as interacting with any location-efficiency variable. Such an interaction would suggest that location efficiency's effect on VMT varies for different income groups. Since none of the referenced studies described testing for such interactions, the lack of evidence for income and location-efficiency interactions in the literature cannot be taken as a lack of such interactions on the ground. Holtzclaw et al. (2002) did find income and location-efficiency interactions using a bounded power fit model on data aggregated at transportation analysis zone level. This formulation does not facilitate ascribing interaction coefficients to the household level.

Finally, most authors included the raw income data in their model with no adjustments. Murakami and Young (1997) did adjust their data by the family size and Bento et al. (2005) adjusted their data to subtract the fixed costs of car ownership. No study distinguished between purchasing power in different regions. Since the value of money varies by place and time and the availability of disposable income varies by family size, there is need for more nuanced adjustments than has been common.

This study seeks to explicitly interact income with location-efficiency variables and express income as a step function that is adjusted for household size and regional purchasing power.

Methodology

This quantitative research first combines travel-survey, transit-service, and land-use data to estimate and explicate an ordinary least squares (OLS) regression model of household VMT. This research then applies the model to census data to predict the VMT of California residents of location-efficient areas.

VMT Model Estimation

Data

The 2010-2012 California Household Travel Survey (CHTS) provides the core data set for the model estimation. This expansive effort collected one-day travel diaries for 42,420 households between January 2012 and February 2013. The CHTS oversampled lower-income, transit-proximate, and rural households – all groups of particular interest for this research. Surveys were collected every day of the year (NuStats, 2013). The CHTS data products are made available to authorized researchers via the Transportation Secure Data Center (National Renewable Energy Laboratory, 2015). This resource provides a self-contained environment to analyze the full data set, but safely limits exports to summary statistics.

These data were divided into policy variables and control variables. The policy variables represent the attributes of direct policy interest including VMT, income, regional context, and location efficiency. The control variables represent attributes of the household itself or the time at which that household was surveyed. Table 1 describes the variables included in the final VMT model.

Policy Variables

Vehicle-Miles Traveled (VMT)

This research calculated household VMT from the CHTS data by tallying the road distances of all trips made by members of a household via privately-operated motorized modes – autos, vans, trucks, motorcycles, scooters, mopeds, taxis, hired cars, limousines, and rented vehicles as well as those carpools and vanpools where the respondent used his or her own vehicle and/or traveled with family members. To ensure this tally reflects vehicle-miles traveled and not person-miles traveled in vehicles, all trip distances were divided by the number of family members traveling together.

The road distances available within the CHTS products were calculated by processing the geocoded activity locations with the Google Maps API. Since these geocoded data points are behind a secure server, it was not possible to recalculate travel distances where they were missing or where they were suspect due to unusually large differences between airline and road distances. A spot analysis of the latter showed that the Google Map API had returned some errant distances. To promote data integrity, this research removed households reporting vehicle-trips without an associated road distance (1,877) or where the ratio of the road distance from the Google Maps API to the airline distance between the origin and destination coordinates exceeded specified thresholds, namely less than 0.85 or greater than 5 (2,286). These thresholds were chosen through analyzing a histogram of the ratios.

Two perennial concerns about household travel surveys are whether the travel on the survey day was out of the ordinary and whether the household falsely reported no trips. A spot check of long trips showed some seemingly extraordinary travel behavior, such as driving several hours to pick up a relative returning from Afghanistan. To exclude such potentially exceptional travel, any household that reported a single trip by any mode that was longer than 99% of trips in the full data set (i.e., at least 102 miles) was considered an outlier and removed (3,493).[1] As an additional measure to cull outlying cases, the remaining households reporting the highest 0.2% of VMT were removed from the study set. At the other end of the travel spectrum, households that did not leave their home during the survey day for reasons that were considered departures from typical habits – i.e. illness, being out of town, and bad weather – were removed from further consideration. Similarly, households that stated they did not leave their home, but did not provide a rationale for their lack of travel were removed to avoid possible false claims of zero trip-making. These combined cuts removed 1,833 households from the sample.[2]

[1] Since many of these long trips overlapped with those above that had suspect geocoding, the total number of households removed at this stage was 4,847.

[2] This research ran the final model on the data set that included the households omitted due to their suspect or extremely long trips (many of which are the same trips). The inclusion of these anomalous data reduced the model's coefficient of determination by 42% while increasing its VMT predictions by roughly 20%. These higher predictions did vary slightly between income groups with Extremely Low Income

Income Variables

To provide an 'apples-to-apples' income comparison in a state where purchasing power varies widely, this research converted nominal household incomes into established US Department of Housing and Urban Development (HUD) categories for determining rental-assistance eligibility. This innovative approach better accounts for regional differences in rents and wages, allows the resulting income variable to consistently enter the model, and directly facilitates the translation of the model findings to policy.

HUD (Office of Policy Development and Research, 2012) publishes these qualifying income thresholds for each county for a family of four for three categories: Extremely Low Income (ELI), Very Low Income (VLI), and Low Income (LI). These categories generally correspond to thresholds of 30%, 50%, and 80%, respectively, of the county's Median Family Income (MFI) with a 'family' defined as a householder living with at least one other person related by birth, adoption, or marriage. This paper follows the many jurisdictions, including the state of California, which refer to HUD's MFI values as the Area Median Income (AMI). HUD also provides a set of factors to adjust qualifying incomes for household size. For example, a one-person household can earn no more than 70% of the threshold value for a four-person household to qualify in the same HUD category. California builds on this system by commonly adding two additional categories: Moderate Income (MI) from 80 to 120% of AMI and Middle Income (MdI) from 120 to 150% of AMI.

This research combined CHTS information on household income (using the midpoints of the selected CHTS income brackets), location and size to identify the appropriate HUD Fiscal Year 2013 category for each household (Office of Policy Development and Research, 2012). Given the importance of income to the current study, CHTS households that did not report their inclusion in one of the ten available income brackets (3,642) were dropped from further consideration. Non-reporting

household VMT rising 22% while High Income household VMT rising 16%, on average. This research selected a more accurate model at the possible risk of more conservative VMT predictions.

of income is a common occurrence in such surveys, particularly when administered by an interviewer, as the CHTS was.

Regional Context Variables

This research follows the literature in recognizing that regional patterns structure travel (Handy, 1993) and in desiring to characterize those patterns (Giuliano, Agarwal, & Redfearn, 2008; Salon, 2013). Exploration of a recent approach that characterized California into eight regions – the four major metropolitan centers and four surrounding geographical areas (Salon, 2013) revealed that the metropolitan centers, regardless of their location, demonstrated similar VMT impacts. This finding led to a more parsimonious tripartite classification of Rural Areas, Metro Regions, and Small Cities, shown in Figure 1.

Rural Areas comprise all lands eligible for US Department of Agricultural (USDA) housing assistance as of February 2, 2015, i.e. fewer than 35,000 inhabitants and rural in character (*Agriculture Act*, 2014). The USDA subsidy also makes this geography immediately relevant for housing policy. Metro Regions comprise the USDA ineligible portions of US Census Urban Areas that intersect at least one municipality with at least 150,000 residents and sufficient transit resources to get those residents to at least 90,000 jobs within a half hour based on posted transit schedules. Small Cities comprise those non-Rural Areas that do not meet the qualifications for Metro Regions.

Location-Efficiency Variables

This research tested an array of location-efficiency variables before selecting three for inclusion in the final model: employment density, transit availability, and neighborhood commute distance. These variables consider VMT as a function of the availability of amenities for non-work purposes, the ease of travel by transit, and the distribution of regional employment opportunities in relation to the household's neighborhood.

Employment density measures jobs per acre within a half mile of the household and is a proxy for neighborhood amenity availability. Households with more neighborhood amenities are expected to drive less as they do not need to travel as far to reach a range of activity locations and can substitute transit or non-motorized modes for these relatively short trips. This proxy for neighborhood amenity, employment density, is calculated by buffering a household with a half-mile radius and including jobs from the underlying US Census Block Groups based on the proportion of each block group covered by that buffer. The underlying job data come from the Longitudinal Employer-Household Dynamics (LEHD) data provided by the US Census Bureau. Different combinations of the twenty industry classifications that the LEHD provides were explored; however, the total job density remained the dominant and most easily-understood measure.[3] To adjust for diffusion across two-dimensional space and its positive skew, employment density entered the model as its fourth root.

Transit availability measures the sum of vehicles on all the fixed-route transit lines by direction that stop within a half-mile of the household over the course of a week. Households with greater transit availability are expected to, on average, use transit more and drive less. The underlying transit route and schedule information come from the Center for Neighborhood Technology's (CNT's) AllTransit™ repository. AllTransit is the most comprehensive general transit feed specification (GTFS) database for the United States. To develop this repository, CNT compiles publicly-available feeds, acquires feeds that exist but are not publicly-available, and codes its own feeds where none exist or are available. The 135 transit systems included in this analysis are listed alphabetically in Table 2. While this list covers the overwhelming majority of transit service for California, there are a few small systems without GTFS data. Furthermore, by its nature, GTFS does not currently capture the demand-responsive services that account for a disproportionate amount of the relatively-limited transit provision in rural communities. In combination, these characteristics may slightly underestimate the full impact of transit, and

[3] This measure was selected as a superior approach to an initial attempt to characterize amenity access by aggregating geo-coded activity locations (e.g. schools, food retailers, health care facilities, etc.). Employment density is more inclusive than a narrow set of activity locations and also provides information on the intensity of activities at those locations. By contrast, a major supermarket and a neighborhood grocery would enter the activity location approach with the same weight in the geo-coding method, obscuring the actual access to amenity.

possibly more so in the rural portion of the state. To adjust for its positive skew, transit availability was transformed and entered the model as its log.

Neighborhood commute distance measures the typical distance from home to work of commuters in the household's neighborhood and is meant to reflect how the regional employment opportunities interact with local preferences to structure travel associated with work. This measure provides a proxy for regional location efficiency as well as jobs-housing mismatch. Households that live in places with lower neighborhood commuting distances are expected to drive less in general as their fixed travel range, as defined by the work and home anchor locations, is reduced. This variable is calculated by drawing a half-mile buffer around the household and then averaging the median commute distance for each block group within that buffer weighted by the number of commuters expected to fall within the buffered portion of each block group. These distances are drawn from the LEHD Origin-Destination Employment Statistics (LODES) data provided by the US Census Bureau. The block group median commute distance measures themselves are calculated as an average of the block-level median commute travel distances weighted by the number of commuters in each block. To adjust for its positive skew, neighborhood commute distance was transformed and entered the model as its log.

This framing of employment density and neighborhood commute distance is distinct from other research. The existing variation in the measure of access to jobs within studies of VMT suggests that the field has not come to agreement on the best way to represent this idea. This study argues that jobs represent both activity *and* employment locations and seeks to decompose its measures of job access to capture that distinction. Furthermore, this study seeks to identify measures that are comparable throughout the entire state rather than just within a single metropolitan region which is why more common 'gravity' measures of job access were excluded.

Control Variables

Household Variables

Household variables control for the distinct composition of respondent households. This research controls for whether any household member was disabled as that status is both associated with reduced driving and an important category for subsidized housing. This research also controls for the number of adult students and the numbers of employed members of a household as both studying and working are activities that are positively associated with travel. One challenge of controlling for household variables is to best represent both the number of people and the life stage of a household. After separating these elements, this research found a more straightforward formulation was to count the number of household members in different age bins, specifically preschoolers (under 6), schoolchildren (6-17), adults (18-64), and seniors (65+). Whenever a CHTS respondent failed to provide his or her age, a common occurrence on surveys, ages imputed by a published post-hoc analysis on the statewide data were used (Metropolitan Transportation Commission, 2013).

Time of Survey Variables

Much research has shown that travel patterns vary across the days of the week as well as seasonally (Hymel, 2014). To account for such variation, this research coded the survey days in several manners. All the days of the week were coded separately, a second coding distinguished weekend days from weekdays, a third coding identified national holidays that occurred on weekdays (such as Thanksgiving) as well as commonly taken vacation days (such as the Friday after Thanksgiving), and a fourth coding distinguished surveys taken in summer (defined as May, June, July, and August) from the rest of the year. Of these, only the Saturday, Sunday, and weekday holiday coding remained significant in the model.

Descriptive Statistics

Table 3 presents variable means by income and Regional Context category. Notably, the sample contains many households in each income and Regional Context category allowing for detailed statistical analysis.

Sample households in Rural Areas drive more than those in Small Cities and Metro Regions although the range between the highest and lowest income groups in the Rural Areas, in both absolute and relative terms, is the smallest. The three measures of location efficiency are starkly different in the three Regional Contexts with Rural Areas reporting the lowest values and Metro Regions reporting the highest values – with no overlapping mean values. Using the Moderate Income households, which include the median, as a breakpoint, the lower-income households report living in more location-efficient sites for employment density and transit availability than higher-income households in all three Regional Contexts; however, in Rural Areas and Small Cities, the lower-income household live in neighborhoods with longer average commute distances than higher-income households. This relationship is reversed in Metro Regions with higher-income households living in neighborhoods with longer average commute distances.

Model Estimation

VMT has two unique traits that complicate statistical modeling. First, VMT cannot fall below zero, and, second, many households report zero VMT. These features result in a distribution of VMT values that diverges from assumptions of normality and raises questions about using traditional ordinary-least squares (OLS) regression. For this reason two recent studies have employed a Tobit regression which is designed for such 'corner solution' situations – i.e., where many respondents select the lowest possible value (Boarnet et al., 2011; Salon, 2013). This research initially pursued the Tobit option as theoretically most appropriate but found that in practice the transformations to the dependent variable that were necessary to meet the Tobit model's stringent requirements for normality resulted in poor prediction of VMT. A series of other regression formulations aimed at addressing 'corner solution' challenges were attempted including Heckman models (also called Tobit II), combined logit and OLS models, and zero-inflated models. A second set of explorations examined regression models for non-Gaussian distributions, such as exponential and Poission distributions as well as non-parametric Cox models. None of these approaches, despite compelling theoretical justifications, yielded superior predictions than the traditional OLS approach, which was chosen for the final model. An additional benefit of OLS is the coefficients can be directly interpreted and their policy implications more readily understood and applied.

OLS models of VMT commonly log-transform the dependent variable (e.g. Bento et al., 2005). This approach was also attempted and resulted in a higher model goodness-of-fit than the untransformed model; however, when the fitted values of the log model were exponentiated and compared to actual household VMT, the coefficient of determination was less than that of the untransformed model. Given the importance of prediction to this research, the final OLS model incorporates actual and not log-transformed VMT.

Initially, separate VMT models were estimated for each of the three Regional Contexts. This approach, however, made it difficult to directly understand where and how relationships varied significantly among those different Regional Contexts. To facilitate comparison and preserve a large data set, the final model considers all the data together while including extensive interactions for Regional Context.

This research followed typical modeling practice to not weight the underlying data if the variables used to generate the weighting factors are themselves included within the statistical model, which they are.

The model estimation expressly does not incorporate explicit measures of residential selection. As Boarnet et al. (2011) note "residential selection has become possibly the central methodological issue in this [land use and travel] literature." Residential selection refers to the idea that households choose a place to live, in part, because of the type of travel they would like to pursue. Therefore, excluding this information may lead to spurious statistical relationships that could challenge model claims to causality. While different approaches to controlling for residential selection within an econometric framework have been well documented (Cao, Mokhtarian, & Handy, 2009), none are particularly satisfying for a cross-sectional study. This research takes a different tack of neither modeling self-selection nor claiming causality. Rather, like Boarnet et al. (2011) cited above, this work is interested in advancing research on other questions. This exclusion neither detracts from the statistical associations nor the predictive ability of the regression model.

Table 4 presents the estimated model parameters. All of the parameters are statistically significant and have the expected signs. The final model included 32,368 responses (76% of the total CHTS sample) and, based on its R^2 goodness-of-fit statistic, accounts for 18.5% of the variation in that underlying data, similar to other studies of single-day travel surveys (cf. Bento et al., 2005; Boarnet et al., 2011; Cervero & Kockelman, 1997; Chatman, 2013; Giuliano & Dargay, 2006; Khattak & Rodriguez, 2005; Salon, 2013).

Findings

This section applies the model to illustrate its findings regarding the role of income and location efficiency, separately and together, on VMT. To isolate these relationships for this analysis, the household variables are all held constant at the statewide averages and the location-efficiency variables are held constant (except when they are the variable of interest) at the median value experienced by households in the given Regional Context.

To determine those ‘experienced’ values, a 200 meter by 200 meter grid (roughly 10 acres or the size of a San Francisco city block) was overlaid on the entire state and relevant location-efficiency values were calculated at the centroid of each grid cell. The number of households in each census block was assigned proportionately to each grid cell based on the share of the block overlapping the grid cell. The cells were grouped by the Regional Context of their centroid and then ranked in order for each location-efficiency variable. The households were counted in order and, at each thousandth quantile (permille) of household for each Regional Context, the associated location-efficiency variable value was identified. The 500th of these household-weighted permilles therefore represents the median value actually experienced by households in each Regional Context and is used with other permille values, as noted below.

Income

This research affirms that, controlling for location efficiency and household variables, income remains a significant, positive predictor of VMT. To calculate the absolute magnitude of these impacts, Table 5 presents modeled VMT for each income group for each day and aggregated for an entire year. By controlling for all variables, except income, the variation in these numbers is attributable to income alone.

A weighted mean of the days in the year shows that, on average, VMT increases monotonically with income. The model predicts that High Income households making more than 150% of AMI, $97,650 for the average-size household in the state capital of Sacramento, drive 19 miles-a-day more than identically-composed Extremely Low Income households making 30% of AMI, $19,550 in Sacramento (income levels derived from HUD's Office of Policy Development and Research, 2012). Over the course of a year, these differences sum to more than 6,900 miles – the equivalent of driving from Key West, Florida to Seattle, Washington and back.

Figure 2 presents these model results in comparison to the median income household (here represented by the Moderate Income group). In Metro Regions, home to two-thirds of California's population, identically-composed and located Low Income households are predicted to drive 10% less than the median, Very Low Income households 25% less, and Extremely Low Income households 33% less. By contrast, Middle Income households are predicted to drive 5% more and High Income households 14% more. The patterns are similar for the other two Regional Contexts, although the differences are slightly reduced in Rural Areas.

Location Efficiency

This research also affirms that, controlling for income and household characteristics, location efficiency remains a significant, negative predictor of VMT. Figure 3, below, illustrates this point by demonstrating the absolute reductions in daily VMT predicted with improved location efficiency. These graphs show the change from the 1st to the 950th permille (95th percentile) for each location-efficiency variable, while holding the other location-efficiency variables constant at the Regional Context median level. (This order is reversed for neighborhood commute distance to reflect increased location efficiency.) The household-weighted median values for each Regional Context are marked with a dot on the bottom of the chart.

The median location-efficiency values, shown by the dots, are substantially lower than the highest values suggesting ample precedent within the existing built environment for reducing VMT through location-efficient living. For example, moving from the 50th percentile (median) to the 60th percentile for employment density in a Metro Region, i.e. living in an area with 444 more workers in the half-mile buffer (less than one additional worker per acre) surrounding the household, is associated with a reduction in expected household VMT by two-thirds of a mile per day or more than 240 miles per year. The median location-efficiency values all occur where small improvements in such efficiency continue to yield deep reductions in VMT.

The Regional Context frames the existing location-efficiency conditions and the relationship of location efficiency to VMT. Rural Areas and Small Cities have similar median values for employment density and transit availability while Small Cities and Metro Regions have more similar median values for neighborhood commute distance. These distinctions extend to the predicted VMT impact of location efficiency. For example, the same level of employment density is associated with less VMT in Rural Areas than in Small Cities and less VMT in Small Cities than in Metro Regions. Finally, the relationship of neighborhood commute distance and household VMT in Rural Areas is relatively weak compared to the other two Regional Contexts – even over a much larger range of commute distances. This observation may suggest that non-work trips are more significant drivers of household VMT in Rural Areas.

Income and Location Efficiency

A key concern of this research is whether income and location efficiency interact in predicting VMT. Such interaction would suggest that location-efficiency characteristics are associated with different levels of VMT for different income groups and might definitively support or refute current California policy which uses location-efficient affordable housing as a climate strategy. This research finds

that given the formulation of location-efficiency variables at a half-mile radius from the household, there were no statistically significant income and location efficiency interactions.[4] This finding is consistent with the literature cited earlier.
The lack of statistically significant interactions found between income and location efficiency suggests that location-efficiency characteristics have commensurate absolute impacts on the VMT of all households regardless of income.

Application to Census Data

The model parameters discussed above suggest that, all things being equal, there is no reason to expect the VMT associated with different levels of location efficiency to vary by income group. However, in reality, all things are not equal, and a consideration of those differences in reality is critical to determining the validity of the location-efficient affordable housing as a VMT reduction strategy. To consider these differences on the ground, this analysis applies the VMT model to US Census Bureau data on households in California's Metro Regions.

Combining the regression model with actual census data provides a more robust basis for considering the allocation of location-efficient space as a VMT reduction strategy. This approach incorporates household data to better touch upon issues of who selects location-efficient living and how their household characteristics (and use of space) might affect VMT. Specifically, this analysis uses census data to identify residential selection and the dwelling space demands of different households in location-efficient areas – information not readily available in the CHTS sample.

Data

This analysis uses the US Census Public Use Microdata Sample (PUMS) records for California from 2012 to best align with the CHTS survey data. PUMS represent all American Community Survey (ACS) data collected for residents of a Public Use Microdata Area (PUMA). PUMAs are non-overlapping areas, coterminous

[4] Interacting all the income dummy variables with all the location-efficiency variables only led to one pairing with an alpha of less than 0.100. This was between Low Income households and employment density and had a significance score of 0.078 – above the 0.050 alpha thresholds for inclusion.

with census block groups, which are designed to incorporate roughly 100,000 residents. The PUMS data for each surveyed household are available at the PUMA geography.

This analysis follows the California approach of using transit availability as a proxy for location efficiency. To identify the households living in the most transit-rich areas, this research flagged each PUMA for which 70% of households live in block groups with a transit availability score of at least 2,000 transit vehicles passing by per week. The block group scores were calculated by proportionally averaging the transit availability values from the underlying grid cells. This method effectively discounts areas such as mountains or parks that take up space, but have little population, to focus on the transit availability experienced by residents. The qualifying 24 transit-rich PUMAs, shown in red in Figure 4, account for 9.7% of California households. These areas include higher- and lower-income neighborhoods of San Francisco, Los Angeles, and San Diego, and constitute a location-efficient geography with full data on the inhabitants.

Using the same approach described earlier for the CHTS data, each PUMS household was assigned to one of the six HUD income groups. The households in each income group were then subdivided into three clusters to reflect household composition: Adults, Families, and Seniors. The presence of children determined inclusion in the Families cluster. For households without children, if the ratio of senior citizens to middle-aged adults was above one, then that household was grouped in the Seniors cluster otherwise that household was grouped into the Adults cluster.[5]

Household Composition

Table 6 presents average household composition values for each income group and cluster of the transit-rich areas using household weights provided by the census. That composition varies in ways that affect VMT.

[5] The composition of these household clusters were determined as common sense household make up, after using a k-cluster analysis to examine how the surveyed households grouped themselves.

Table 7 presents expected annual VMT for each of the clusters and income groups living in the transit-rich PUMAs. To isolate the impact of household composition, the first two columns artificially code every household as Moderate Income, representing the median, in order to remove the income effect from the prediction. Even without considering income, all of the Extremely Low and Very Low Income (and most of the Low Income) clusters in transit-rich areas are modeled to drive less than the median household. This phenomenon occurs because these households are more likely to be composed of members, such as the disabled or non-workers, who generate less VMT. These impacts are substantial. For example, based on household composition alone and excluding income, an Extremely Low Income Senior household is predicted to drive 30% fewer miles than the median, while a High Income Senior household is predicted to drive 21% more miles than the median. Incorporating the actual income effects, as shown in the last two columns of Table 7, magnifies these predicted VMT differences. Comparing these values to those presented in Figure 2 demonstrates how the added information on the actual composition of households in transit-rich areas generally results in larger differences from the median than using statewide average characteristics. For example, where Figure 2 reported that, with statewide average household characteristics, an Extremely Low Income household in Metro Regions would predict driving of 33% less than the median, Table 7 suggests that this reduction could be 54% when considering household characteristics of the households in transit-rich areas.

Residential Space Demand

Allocating scarce, location-efficient space should take into account which populations use that space most efficiently. The PUMS data include information on car ownership, rooms per dwelling unit, and dwelling units per building for each household. These three measures all link to different demands for residential space, namely parking, household living area, and land take. While the data are not sufficiently specific to provide precise measurements of space used, taken together they do suggest the general magnitude of the varying spatial demands, by income and cluster, of location-efficient households.

To present dwelling units per building consistently with the other two spatial indicators, i.e. with larger numbers representing demands for more space and lower numbers representing demand for less space, this measure is inverted to represent the share of a building taken up by a single dwelling unit. The PUMS data provides units per building information through an ordinal series of residential categories (i.e. 1-unit detached, 1-unit attached, 2-units, 3-4 units, 5-9 units, 10-19 units, 20-49 units, and 50+ units). This research takes the inverse of the midpoint for each category. Based on discussions with urban housing professionals in California, the midpoint for the largest building category is assumed to be 100 units.

Table 6 shows that lower-income households own fewer cars, live in fewer rooms, and take up smaller shares of their buildings. Table 8 presents the percentage difference of these values from the median as represented by the Moderate Income group. These values are always negative for the lower-income groups, demonstrating their reduced spatial demands, and almost always positive for the higher-income groups demonstrating their higher spatial demands. For example, the average Extremely Low Income Family in a transit-rich area demands 55% less parking, 24% fewer rooms, and 34% less building space than the median while the average Middle Income Family in those same transit-rich areas demands 5% more parking, 8% more rooms, and 3% more building space than the median.

The building space measure is most pertinent to the consideration of the allocation of scarce location-efficient land. Lower-income groups simply use location-efficient space more efficiently. This efficiency extends the VMT reduction benefits of any parcel to more households.

Figure 5 illustrates this point through a thought experiment. It represents the predicted annual VMT reduction associated with developing a parcel within the transit-rich area for the average households, by income and cluster, currently living outside the transit-rich area (but within the Metro Regions). The household characteristics are based on a weighted average, by income and cluster, of the PUMS data from the non-transit-rich PUMAs. The initial location-efficiency characteristics are based on PUMA averages weighted by the number of households, by income and cluster, in each PUMA. The final location-efficiency characteristics are based on PUMA averages weighted by all households (i.e. to provide the same values). The VMT model is used to calculate the annual VMT for a single household in both locations. Those benefits are then aggregated by the number of households, by income and cluster, which live in a typical building in transit-rich areas.

Figure 5 shows that in all cases, a parcel aimed at lower-income households results in greater VMT reductions than developing the same parcel for higher-income households.

Policy Implications

This research finds that both income and location efficiency are independently associated with VMT, but that those relationships do not interact. While the lack of interactions suggests there is no theoretical reason to favor one income group over another for the most location-efficient sites, an analysis of actual population distribution suggests that lower-income households will use those sites more efficiently to yield a higher VMT reduction.

While these findings support California's AHSC in general, they raise questions regarding specific aspects of the project evaluation process. The AHSC program relies on the California Emissions Estimator Model (CalEEMod) to assess applications (Strategic Growth Council, 2015). CalEEMod's approach to assessing VMT reductions for different mitigation measures is based on the user-friendly guidance developed by the California Air Pollution Control Officers Association (CAPCOA). The CAPCOA method for calculating the VMT reduction of affordable housing is to multiply the share of below-market rate (BMR) units in a development by 0.04 (California Air Pollution Control Officers Association, 2010). For an entirely-BMR development, this approach estimates a 4% VMT reduction over an otherwise-similar market-rate development. This assumption is far less than the reductions predicted by this analysis of California data – either for an average household or for the lower-income households living in transit-rich PUMAs. This research would recommend increasing VMT reductions attributable to lower incomes and adding more gradation to consider different income levels, different Regional Contexts, and different household compositions. Ideally, statistical models, such as the one presented here, should be used to estimate VMT for new construction.

The 2014-15 AHSC Guidelines (Adopted 1/20/2015) sets a threshold of being within a 12-mile distance of a major job center defined as having more than 5,000 jobs per square mile. Such a standard is too limited. It does not take into account the importance of highly localized amenities that are strongly associated with reduced VMT. It does not take into account regional variation, such as the limited sensitivity of households in Rural Areas to changes neighborhood commute distances. And it does not take into account that outside of Metro Regions, few centers would meet this standard, while other interventions could attain comparable VMT reductions. Thresholds are useful for establishing standards, but those standards should be closely tied to evidence of the current impacts of land use on travel behavior in California.

Conclusions

This research finds that location-efficient affordable housing is an effective climate strategy. Developing parcels for lower-income households in location-efficient areas is likely to lead to higher reductions in VMT than developing those parcels for higher-income populations. The cause of this difference is not that lower-income households show greater VMT reduction with location efficiency because VMT reduction is consistent across income groups, but that lower-income households live more compactly in location-efficient areas – allowing each parcel to yield more VMT reduction.

Polices, such as the California AHSC, offer effective means to reduce VMT; however, care must be taken to align the implementation of those policies with the factors that actually contribute to reduced VMT. The statistical model presented by this research provides a nuanced approach to explicating those relationships as well as for estimating VMT for a given household in a given location.

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Any errors remain the responsibility of the authors.

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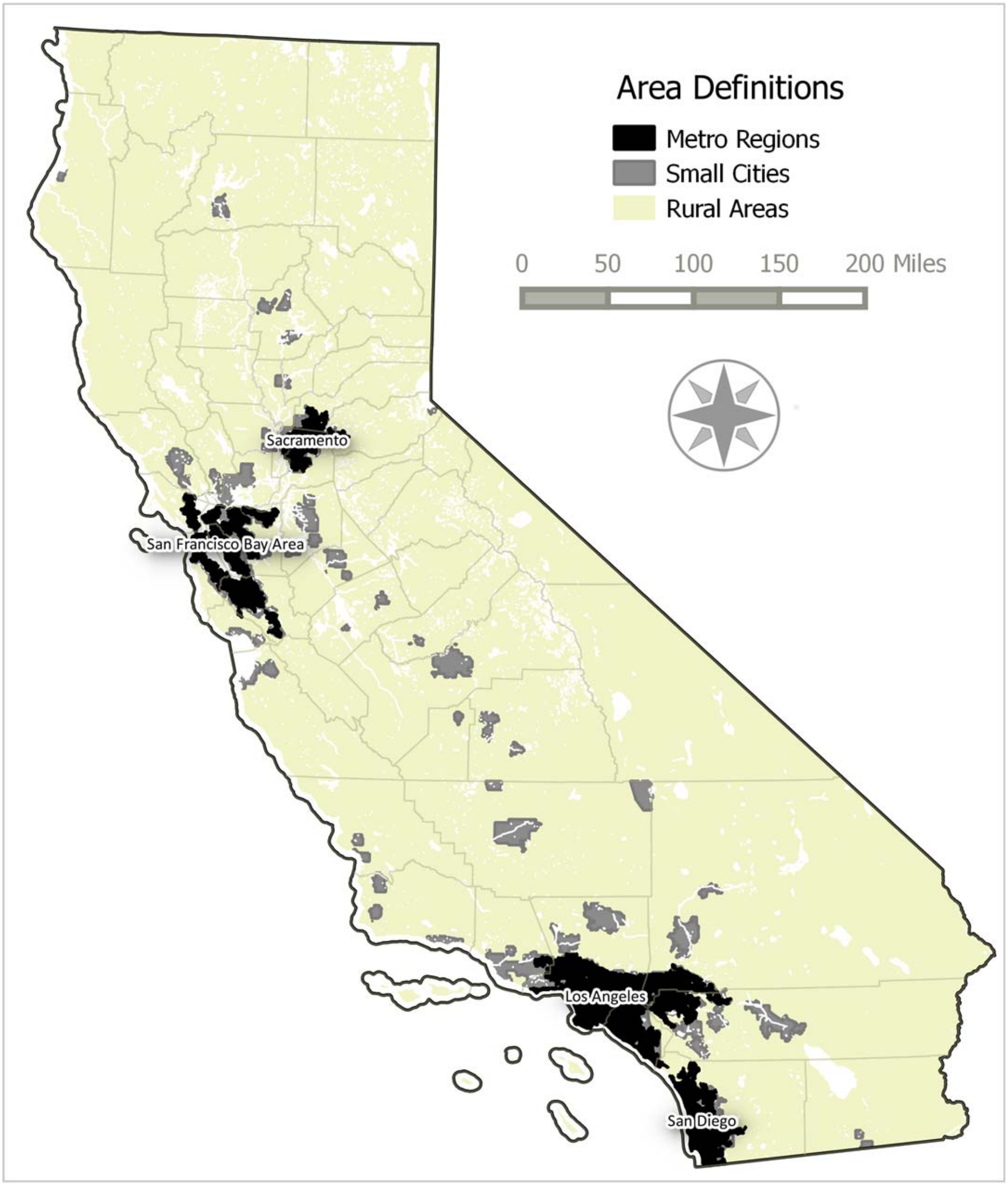
Figure 1. Map of Study Area



Note: Population Data – Metro Regions (24,865,551), Small Cities (7,922,024), Rural Areas (4,532,683)

Table 1. Variables in Statewide VMT Model

Variables	Description
VMT	Vehicle-miles traveled for a single household for a single day.
Income	
Extremely Low Income (ELI)	Household earns less than 30% of AMI
Very Low Income (VLI)	Household earns between 30% and 50% of AMI
Low Income (LI)	Household earns between 50% and 80% of AMI
Moderate Income (MI)	Household earns between 80% and 120% of AMI
Middle Income (MdI)	Household earns between 120% and 150% of AMI
High Income (HI)	Households earns more than 150% of AMI
Regional Context	
Rural Area	Areas eligible for housing assistance from the USDA
Metro Region	Non-Rural Areas composed of U.S. Census Urban Areas with a municipality of at least 150,000 residents who, on average, can reach at least 90,000 jobs in a half-hour on transit.
Small City	All non-Rural Areas that do not qualify as Metro Regions
Location Efficiency	
Employment Density	Density of jobs recorded in LEHD within a half mile of the household. (Expressed as jobs / acre)
Transit Availability	The number of transit vehicle runs (in each direction) stopping within a half mile of the household in a typical week
Neighborhood Commute Distance	Weighted average of median commute block group distances within a half mile of the household.
Household	
Disability in HH	Household has a disabled member.
Adult Students	Number of adult (18-64) students in household.
Workers in HH	Number of employed workers in household
Preschoolers in HH	Number of children (0-5)
Schoolchildren in HH	Number of school-age children (6-17)
Adults in HH	Number of adults (18-64) in household
Seniors in HH	Number of senior citizens (65+) in household
Time of Survey	
Saturday	Travel day is Saturday
Sunday	Travel day is Sunday
Holiday	Travel day is a weekday holiday (e.g. Christmas)

Table 2. California Transit Services Analyzed (Fixed Route Only)

Transit Agencies
Alameda-Contra Costa Transit District - AC Transit, Alhambra Community Transit, Alpine Meadow Shuttle, Altamont Commuter Express (ACE), Amador RTS, Arcata & Mad River Transit, Atascadero Transit / North County Shuttle, Avila Trolley, BART (Bay Area Rapid Transit), Baylink Ferry, Beach Cities Transit - City of Redondo Beach (BCT), Beaumont Transit System, Beeline, Bellflower Bus, Big Blue Bus, BlueGo, Burbank Bus, Bus Line Service of Turlock, Butte Regional Transit (B-Line), Calaveras Transit, California Shuttle Bus, Caltrain, Camarillo Area Transit, Capital Corridor, Ceres Area Transit, Cerritos on Wheels (COW), Chula Vista Transit (CVT), City Coach, City of Baldwin Park Transit, City of Commerce Municipal Buslines (CBL), City of Corona Transit Services (CCTS), City of Menlo Park Shuttles, City of Petaluma Transit, City of Visalia Transit, CityLine, Cloverdale Transit, COLT (City of Lincoln Transit), COLT (City of Lompac Transit), County Connection (Central Contra Costa Transit Authority), Dinuba Transit, DowneyLINK, Eastern Contra Costa Transit Authority, Eastern Sierra Transit Authority, El Dorado County Transit Authority, El Sol Shuttle, e-tran (Elk Grove), eTrans (Escalon), Eureka Transit Service, Fairfield-Suisun Transit System, Folsom Stage Line, Foothill Transit, Fresno Area Express, Go West, Gold Coast Transit, Gold County Stage, Golden Empire Transit District, Golden Gate Transit, Grapeline (city of Lodi), Healdsburg Transit, Irvine Shuttle, Kern Regional Transit, Kings Area Rural Transit, La Puente Link, LADOT, Laguna Beach Municipal Transit (LBMT), Lake Transit, Lassen Rural Bus, Lawndale Beat, Long Beach Transit, Los Angeles County Metropolitan Transportation Authority (Metro), Madera County Transit, Marin Transit, MAX (Modesto Area Express), Mendocino Transit Authority, Merced County Transit - The Bus, Metro (Santa Cruz Metropolitan Transit District), MetroLink (Southern California Regional Rail Authority), Monterey-Salinas Transit (MST), Moorpark CityBus, Morro Bay Transit, Mountain Transit, MTS (San Diego Metropolitan Transit System), MUNI (San Francisco Municipal Transportation Authority), Municipal Area Express, North County Transit District (NCTD), Omnitrans, Orange County Transportation Authority, Palos Verdes Peninsula Transit Authority, Pasadena Area Rapid Transit System (ARTS), Placer County Transit, Plumas Transit, Porterville Transit, Redding Area Bus Authority, Redwood Transit System, Rio Vista Delta Breeze, Riverside Transit Agency, Roseville Transit, Sacramento Regional Transportation District, SamTrans (San Mateo County Transportation Authority), San Benito County Express, San Francisco Bay Ferry, San Joaquin Regional Transportation District, San Luis Obispo Regional Transit Authority, Santa Barbara Metropolitan Transit District, Santa Clarita Transit (SCT), Santa Maria Area Transit, Santa Rosa City Bus, Simi Valley Transit (SVT), Siskiyou Transit and General Express (STAGE), SolTrans, Sonoma County Transit, Stanislaus Regional Transit, SunLine Transit Agency (SunLine), Susanville Indian Rancheria Public Transportation Program, Tahoe Area Regional Transit, Tehama Rural Area Express (TRAX), Thousand Oaks Transit (TOT), Torrance Transit System (TTS), Town of Truckee Public Transit, Tracer, Trinity Transit, Tulare County Area Transit, Tulare Transit Express, Tuolumne County Transit, Union City Transit (UCT), Unitrans(City of Davis & UC Davis), Ventura Intercity Service Transit Authority, Victor Valley Transit Authority (VVTA), Vine (Napa County), VTA (Santa Clara Valley Transportation Authority), Western Contra Costa Transit Authority (WESTCAT), Wheels (Livermore/Amador Valley Transit Authority), Yolobus (Yolo County Transportation District), Yosemite Area Regional Transportation System, Yuba Sutter Transit

Note: Data on these 135 systems were all accessed via CNT's AllTransit™ GTFS repository.

Table 3. Mean Variable Values by Income Group and Regional Context

Regional Context	Rural Areas						Small Cities						Metro Regions					
Income Group	**ELI**	**VLI**	**LI**	**MI**	**MdI**	**HI**	**ELI**	**VLI**	**LI**	**MI**	**MdI**	**HI**	**ELI**	**VLI**	**LI**	**MI**	**MdI**	**HI**
Responses	571	1,024	1,061	1,445	919	2,257	859	1,082	1,234	1,399	1,043	2,664	1,927	1,687	2,454	3,323	1,684	5,735
Variables																		
VMT	30.1	27.8	37.9	44.2	49.2	53.4	22.1	22.9	32.5	37.8	41.6	49.1	20.3	24.5	33.1	37.6	43.7	48.0
Location Efficiency																		
Employment Density	0.52	0.41	0.33	0.32	0.30	0.26	2.00	1.92	1.64	1.44	1.34	1.33	7.10	5.76	5.11	5.84	4.05	4.62
Transit Availability	85	62	61	59	51	55	589	488	433	391	332	331	2,867	2,088	1,908	2,053	1,426	1,375
Commute Distance	18.4	18.5	18.2	18.5	17.1	17.2	15.5	14.9	15.4	14.9	14.5	13.9	10.6	11.0	11.0	11.0	11.5	11.2
Household																		
Disability in HH	0.35	0.32	0.24	0.18	0.15	0.10	0.34	0.29	0.23	0.18	0.15	0.09	0.31	0.25	0.18	0.13	0.12	0.08
Adult Students	0.19	0.11	0.14	0.15	0.14	0.12	0.22	0.15	0.21	0.17	0.16	0.16	0.23	0.23	0.21	0.17	0.20	0.15
Workers in HH	0.77	0.71	1.01	1.13	1.26	1.41	0.77	0.70	1.04	1.17	1.25	1.48	0.82	0.90	1.11	1.25	1.43	1.55
Preschoolers in HH	0.29	0.10	0.11	0.11	0.11	0.08	0.29	0.17	0.15	0.13	0.14	0.09	0.19	0.11	0.10	0.12	0.15	0.10
Schoolchildren in HH	0.78	0.34	0.39	0.32	0.29	0.26	0.75	0.36	0.44	0.40	0.35	0.33	0.55	0.43	0.38	0.33	0.45	0.39
Adults in HH	1.71	1.24	1.40	1.50	1.53	1.63	1.65	1.29	1.54	1.51	1.57	1.73	1.60	1.46	1.52	1.53	1.73	1.75
Seniors in HH	0.29	0.50	0.62	0.54	0.54	0.42	0.28	0.44	0.50	0.51	0.53	0.34	0.38	0.47	0.49	0.46	0.39	0.30
Time of Survey																		
Saturday	0.15	0.16	0.15	0.14	0.14	0.14	0.15	0.13	0.13	0.14	0.15	0.14	0.13	0.13	0.14	0.13	0.11	0.14
Sunday	0.17	0.15	0.15	0.16	0.14	0.15	0.18	0.17	0.14	0.15	0.15	0.15	0.14	0.14	0.14	0.15	0.15	0.13
Holiday	0.05	0.03	0.04	0.03	0.04	0.04	0.04	0.03	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04

Table 4. OLS Model of Daily Household VMT

Predictor Variables	Type	Parameter	SE	Sig	Code
(Intercept)		25.052	3.021	0.000	***
Income					
Extremely Low Income (ELI)	Dummy	-13.837	1.526	0.000	***
Very Low Income (VLI)	Dummy	-12.570	1.322	0.000	***
Low Income (LI)	Dummy	-10.323	0.853	0.000	***
Moderate Income (MI)	Dummy	-7.720	0.781	0.000	***
Middle Income (MdI)	Dummy	-3.809	0.782	0.000	***
High Income (HI)	Dummy	Default			
Regional Context					
Rural Area	Dummy	8.436	2.711	0.002	**
Metro Region	Dummy	1.921	0.607	0.002	**
Small City	Dummy	Default			
Location Efficiency					
Employment Density	4^{th} Root	-12.713	1.312	0.000	***
Transit Availability	Log	-2.363	0.455	0.000	***
↘ Employment Density		0.806	0.175	0.000	***
↘ NHBD Commute Distance		0.376	0.145	0.010	**
Neighborhood Commute Distance	Log	5.413	0.962	0.000	***
↘ Rural Areas		-4.172	0.928	0.000	***
Household					
Disability in HH	Dummy	-5.481	0.644	0.000	***
Adult Students	Integer	3.562	0.572	0.000	***
Workers in HH	Integer	7.468	0.365	0.000	***
Preschoolers in HH	Integer	1.338	0.548	0.015	*
Schoolchildren in HH	Integer	5.275	0.359	0.000	***
↘ Extremely Low Income (ELI)		-2.522	0.804	0.002	**
↘ Low Income (LI)		-1.777	0.815	0.029	*
Adults in HH	Integer	8.341	0.437	0.000	***
↘ Rural Areas		2.094	0.541	0.000	***
↘ Extremely Low Income (ELI)		-3.839	0.734	0.000	***
↘ Very Low Income (VLI)		-3.716	0.667	0.000	***
Seniors in HH	Integer	4.189	0.440	0.000	***
Time of Survey					
Saturday	Dummy	-8.170	0.937	0.000	***
↘ Rural Areas		-4.394	1.548	0.004	**
↘ Extremely Low Income (ELI)		4.672	2.229	0.036	*
↘ Very Low Income (VLI)		6.474	2.125	0.002	**
↘ Moderate Income (MI)		4.800	1.781	0.007	**
Sunday	Dummy	-21.325	1.175	0.000	***

↘ Metro Region		5.023	1.284	0.000	***
↘ Extremely Low Income (ELI)		11.944	2.204	0.000	***
↘ Very Low Income (VLI)		12.035	2.131	0.000	***
↘ Low Income (LI)		6.404	1.951	0.001	**
↘ Moderate Income (MI)		7.018	1.757	0.000	***
Holiday	Dummy	-20.726	1.800	0.000	***
↘ Extremely Low Income (ELI)		10.489	3.921	0.007	**
↘ Very Low Income (VLI)		11.614	3.972	0.004	**
↘ Low Income (LI)		10.393	3.572	0.004	**
↘ Moderate Income (MI)		7.987	3.254	0.014	*

Model Information		
Dependent Variable	VMT	
Sample Size	32,368	
F Statistic	176.4	df(42, 32325)
Adjusted R^2	0.185	

Note: Diagonal arrows (↘) connect interaction variables. Sig. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’

Table 5. Predicted VMT by Income Group

Regional Context	Weekday	Saturday	Sunday	Holiday	Average	Annual
Rural Areas						
Extremely Low Income (ELI)	41.8	33.9	32.5	31.6	39.0	14,240
Very Low Income (VLI)	44.5	38.4	35.2	35.4	42.0	15,328
Low Income (LI)	52.4	39.8	37.4	42.0	48.1	17,546
Moderate Income (MI)	55.8	48.0	41.5	43.1	52.2	19,052
Middle Income (MdI)	59.7	47.1	38.4	39.0	54.1	19,761
High Income (HI)	63.5	51.0	42.2	42.8	57.9	21,152
Small Cities						
Extremely Low Income (ELI)	31.1	27.6	21.8	20.9	28.9	10,564
Very Low Income (VLI)	33.8	32.1	24.5	24.7	31.9	11,651
Low Income (LI)	41.7	33.5	26.7	31.3	38.0	13,869
Moderate Income (MI)	45.1	41.7	30.8	32.4	42.1	15,376
Middle Income (MdI)	49.0	40.8	27.7	28.3	44.1	16,085
High Income (HI)	52.8	44.6	31.5	32.1	47.9	17,475
Metro Regions						
Extremely Low Income (ELI)	28.9	25.4	24.5	18.6	27.4	9,989
Very Low Income (VLI)	31.5	29.8	27.3	22.4	30.3	11,077
Low Income (LI)	39.4	31.2	29.5	29.0	36.4	13,295
Moderate Income (MI)	42.8	39.4	33.5	30.1	40.6	14,801
Middle Income (MdI)	46.7	38.5	30.4	26.0	42.5	15,510
High Income (HI)	50.5	42.4	34.2	29.8	46.3	16,900

Note: Average and annual values assume 248 weekdays, 52 Saturdays, 52 Sundays, and 13 Holidays. For all predictions, the households characteristics were held at the statewide mean and the location-efficiency variables were held at the Regional Context median weighted by the distribution of households.

Figure 2. Percentage Difference in Average VMT Attributable to Income

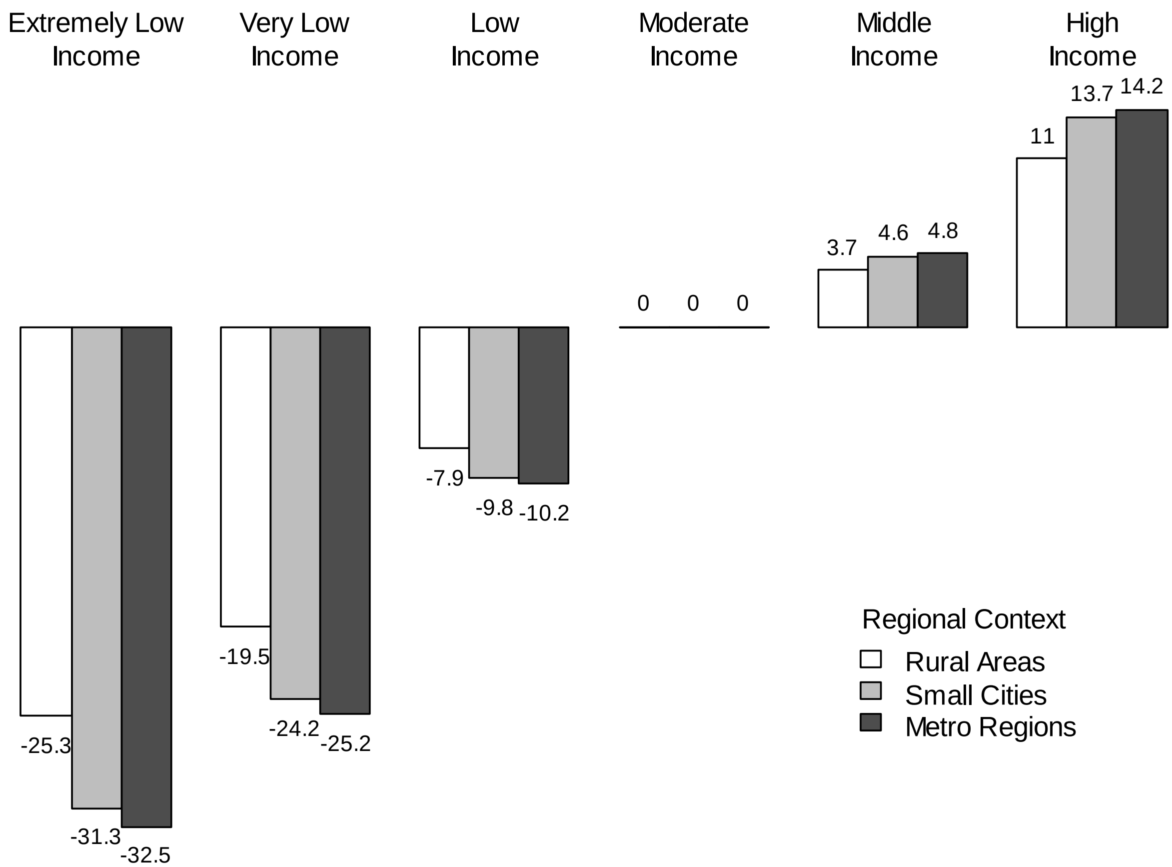
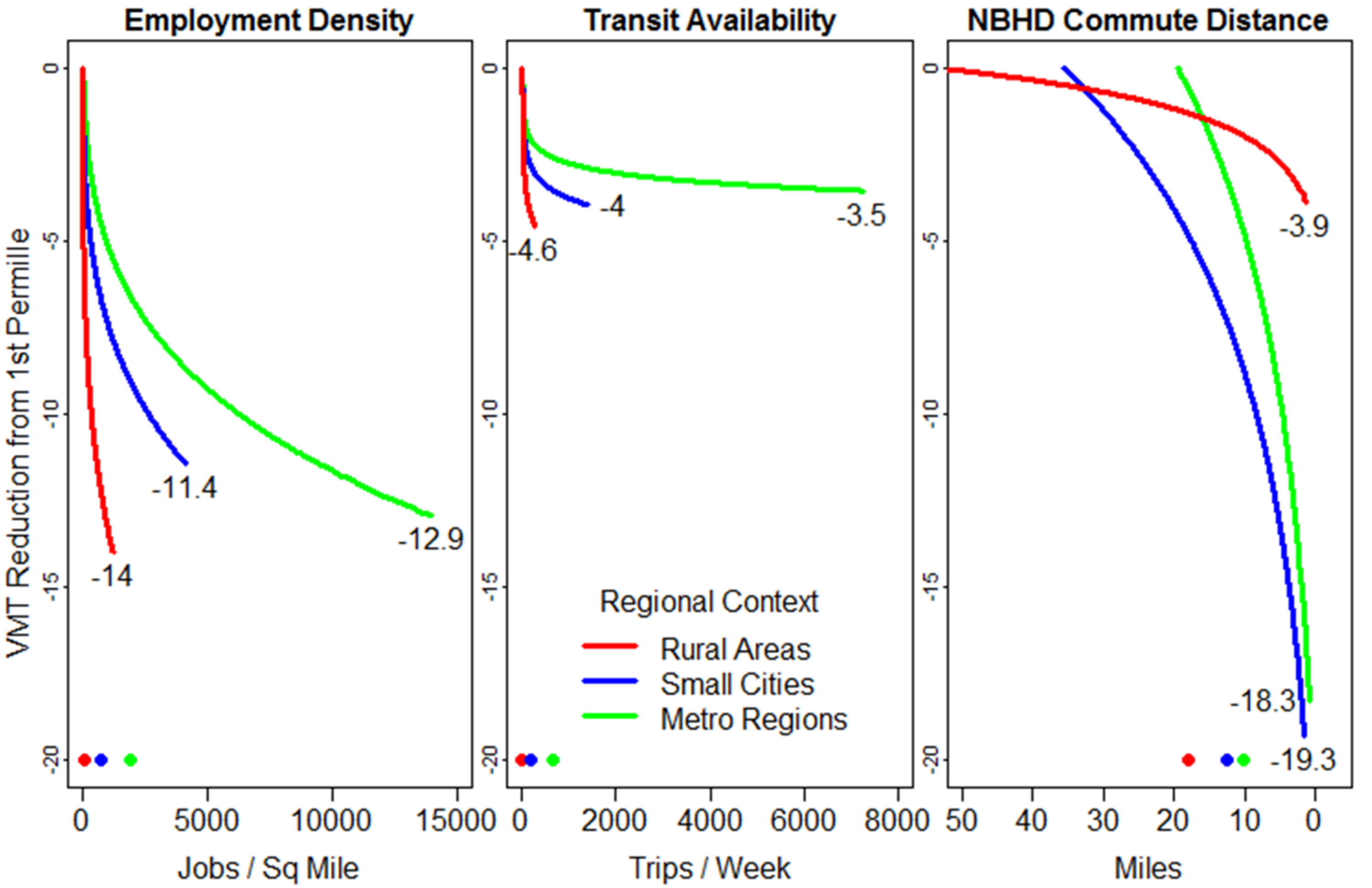


Figure 3. Daily VMT Reduction Associated with Location Efficiency Variables



Dots represent median values of the given location efficiency variable as experienced by households in each Regional Context
Numbers represent reductions at 95th percentile; Data reversed for Neighborhood Commute Distance (i.e. 950th to 1st permille).
Note that Employment Density is a measure of access to amenities.

Figure 4. Transit-Rich PUMAs in California

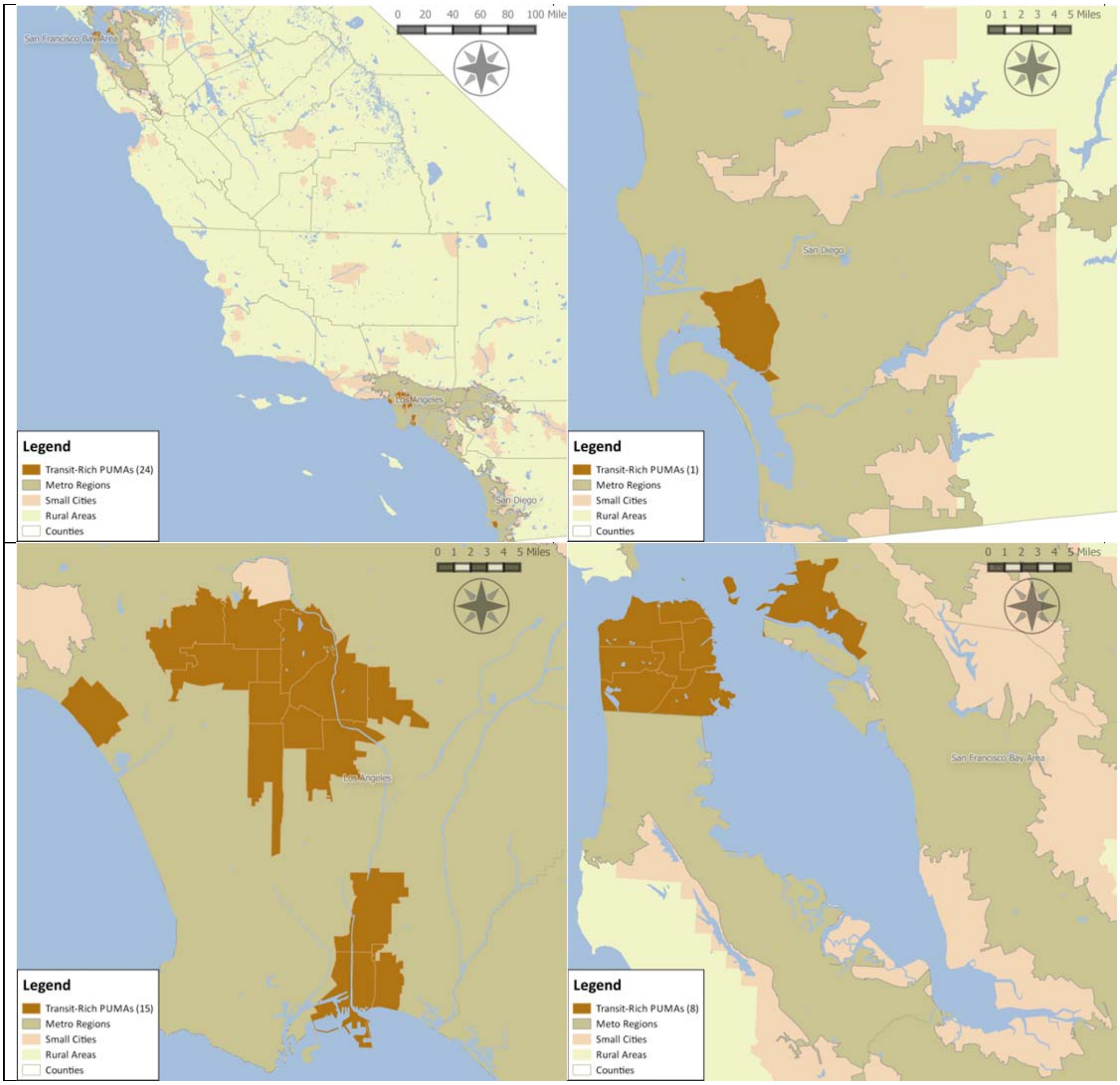


Table 6. Cluster Averages of Residents of Transit Rich Areas

Income Group	Share	Age Cohorts					Occupation		Vehicles and Home					
	% of Group	0-5	6-17	18-64	65+	Total	Work	Study	Cars		Rooms in Unit		Share of Building	
									Per HH	Per Person	Per HH	Per Person	Per HH	Per Person
Extremely Low	**100.0**	**0.2**	**0.4**	**1.2**	**0.3**	**2.2**	**0.9**	**0.3**	**0.7**	**0.3**	**3.3**	**1.5**	**0.33**	**0.15**
Adults	47.9	0.0	0.0	1.4	0.1	1.5	0.9	0.4	0.7	0.5	3.0	2.0	0.28	0.18
Families	28.6	0.6	1.5	1.9	0.1	4.1	1.3	0.3	0.9	0.2	3.8	0.9	0.46	0.11
Seniors	23.6	0.0	0.0	0.0	1.2	1.2	0.2	0.0	0.4	0.4	3.3	2.7	0.30	0.24
Very Low	**100.0**	**0.2**	**0.5**	**1.7**	**0.3**	**2.6**	**1.4**	**0.2**	**1.1**	**0.4**	**3.6**	**1.4**	**0.41**	**0.16**
Adults	51.6	0.0	0.0	1.6	0.1	1.7	1.4	0.3	1.0	0.6	3.3	1.9	0.34	0.19
Families	35.2	0.6	1.3	2.4	0.1	4.3	1.9	0.3	1.4	0.3	4.0	0.9	0.50	0.11
Seniors	13.2	0.0	0.0	0.1	1.4	1.5	0.4	0.0	0.8	0.6	4.1	2.7	0.45	0.30
Low	**100.0**	**0.1**	**0.3**	**1.9**	**0.3**	**2.6**	**1.7**	**0.3**	**1.4**	**0.5**	**4.0**	**1.5**	**0.44**	**0.17**
Adults	62.2	0.0	0.0	1.9	0.1	2.0	1.7	0.3	1.2	0.6	3.6	1.8	0.36	0.18
Families	27.7	0.5	1.2	2.6	0.1	4.5	2.2	0.3	1.7	0.4	4.6	1.0	0.59	0.13
Seniors	10.1	0.0	0.0	0.1	1.4	1.5	0.5	0.0	1.1	0.8	4.9	3.3	0.53	0.36
Moderate	**100.0**	**0.1**	**0.3**	**1.8**	**0.2**	**2.4**	**1.7**	**0.2**	**1.5**	**0.6**	**4.2**	**1.7**	**0.46**	**0.19**
Adults	68.2	0.0	0.0	1.7	0.1	1.8	1.7	0.2	1.3	0.7	3.8	2.1	0.36	0.20
Families	23.7	0.6	1.1	2.6	0.1	4.5	2.3	0.3	2.1	0.5	5.0	1.1	0.69	0.15
Seniors	8.1	0.0	0.0	0.1	1.4	1.5	0.6	0.0	1.2	0.8	4.9	3.3	0.59	0.40
Middle	**100.0**	**0.1**	**0.2**	**1.8**	**0.2**	**2.3**	**1.8**	**0.2**	**1.5**	**0.7**	**4.2**	**1.9**	**0.44**	**0.19**
Adults	76.2	0.0	0.0	1.7	0.1	1.8	1.7	0.2	1.4	0.8	3.9	2.1	0.37	0.20
Families	17.0	0.6	1.1	2.6	0.2	4.5	2.5	0.2	2.2	0.5	5.4	1.2	0.71	0.16
Seniors	6.8	0.0	0.0	0.1	1.5	1.6	0.9	0.0	1.2	0.8	5.1	3.2	0.54	0.34
High	**100.0**	**0.1**	**0.2**	**1.8**	**0.2**	**2.3**	**1.8**	**0.1**	**1.6**	**0.7**	**5.1**	**2.2**	**0.48**	**0.21**
Adults	72.8	0.0	0.0	1.8	0.1	1.9	1.8	0.1	1.6	0.8	4.6	2.4	0.41	0.21
Families	19.7	0.8	0.9	2.2	0.1	3.9	2.0	0.2	2.0	0.5	6.4	1.6	0.72	0.19
Seniors	7.5	0.0	0.0	0.1	1.5	1.6	0.9	0.0	1.4	0.9	5.8	3.6	0.58	0.36

Table 7. Predicted Annual VMT of Residents of Transit Rich Areas

Income Group	Holding Income at Median		Incorporating Actual Income	
	Estimated VMT	% Difference from Median	Estimated VMT	% Difference from Median
Extremely Low	**11,000**	**-0.26**	**6,926**	**-0.54**
Adults	10,709	-0.23	6,768	-0.51
Families	16,505	-0.21	10,473	-0.50
Seniors	4,930	-0.30	2,953	-0.58
Very Low	**14,014**	**-0.06**	**10,373**	**-0.31**
Adults	12,585	-0.09	9,037	-0.35
Families	18,978	-0.09	14,402	-0.31
Seniors	6,319	-0.10	4,819	-0.31
Low	**15,253**	**0.02**	**13,833**	**-0.08**
Adults	14,274	0.03	13,073	-0.06
Families	20,615	-0.01	18,625	-0.11
Seniors	6,526	-0.07	5,325	-0.24
Moderate	**14,957**	**0.00**	**14,957**	**0.00**
Adults	13,840	0.00	13,840	0.00
Families	20,878	0.00	20,878	0.00
Seniors	7,029	0.00	7,029	0.00
Middle	**14,821**	**-0.01**	**15,530**	**0.04**
Adults	14,011	0.01	14,720	0.06
Families	21,163	0.01	21,872	0.05
Seniors	8,113	0.15	8,822	0.26
High	**14,813**	**-0.01**	**16,913**	**0.13**
Adults	14,529	0.05	16,628	0.20
Families	18,283	-0.12	20,382	-0.02
Seniors	8,502	0.21	10,602	0.51

Table 8. Spatial Differences in Transit-Rich Areas

Income Group	Share	% Differences from Median		
	% of Group	Parking Spaces	Rooms in Unit	Building Share
Extremely Low	**100.0**	**-52.7**	**-21.4**	**-27.6**
Adults	47.9	-46.7	-21.7	-23.9
Families	28.6	-55.4	-24.3	-33.7
Seniors	23.6	-64.0	-32.8	-49.9
Very Low	**100.0**	**-27.5**	**-12.8**	**-10.9**
Adults	51.6	-26.8	-14.4	-6.9
Families	35.2	-35.5	-19.0	-27.9
Seniors	13.2	-31.8	-16.9	-23.7
Low	**100.0**	**-9.8**	**-4.4**	**-3.8**
Adults	62.2	-6.9	-5.8	-1.2
Families	27.7	-18.7	-8.3	-13.9
Seniors	10.1	-8.4	-0.1	-9.8
Moderate	**100.0**	**0**	**0**	**0**
Adults	68.2	0	0	0
Families	23.7	0	0	0
Seniors	8.1	0	0	0
Middle	**100.0**	**1.3**	**1.5**	**-4.4**
Adults	76.2	5.2	2.4	1.7
Families	17.0	5.4	8.1	2.8
Seniors	6.8	-0.7	4.8	-9.3
High	**100.0**	**9.7**	**21.5**	**5.1**
Adults	72.8	18.5	21.8	11.9
Families	19.7	-3.3	28.3	5.2
Seniors	7.5	12.9	18.9	-2.0

Figure 5. Annual VMT Reduction Predicted with Move to Transit-Rich Building