Sustainable and Affordable Housing Near Rail Transit: Refining and Expanding a Scenario Planning Tool

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Abstract

What are the travel behavior goals of transit-oriented developments (TODs) and are they achieving them? Does TOD policy fit all goals? This report examines the relationship between travel behavior, transit access, income, and neighborhood type in the context of environmental, system efficiency, and social equity goals. Based on analyses of four metropolitan areas in California, the findings indicate that higher-income households reduce vehicle miles traveled (VMT) most, relative to households in other income categories, when living near transit regardless of neighborhood type. In contrast, lower-income households use the transit system more when living in denser, transit-served neighborhoods. Furthermore, empirical evidence suggests that lower-income households tend to own older vehicles, and are less likely to own hybrid or electric vehicles. Thus, although higher-income households reduce their VMT more relative to lower-income households when living near transit, households' reductions in greenhouse gas (GHG) emissions may be even larger across income categories. In light of these observations, it seems that joint consideration of the needs and behaviors of both higher- and lower-income populations are integral when planning and establishing goals for TODs.

Disclosure

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1. Introduction

Over the past 25 years, living within walking-distance to rapid transit has become en vogue in the U.S. and Canadian contexts. This trend has accompanied the construction and renovation of transit lines across large and medium-sized metropolitan areas. Urban planners have both promoted and capitalized on this trend by encouraging residential and mixed-use development near existing and new transit stations, especially rail stations. Planners have justified this form of development, termed transit-oriented development (TOD), on the grounds that TOD residents will change their travel behavior toward fewer automotive trips and vehicle miles driven and more transit trips. Such a shift would, in turn, reduce the household's environmental impact, and in aggregate, the regional environmental impact from transportation.

In fact, state and regional policies have codified TOD as a tool to reduce VMT and GHG emissions. An example of such state policies is California's Sustainable Communities Act (Senate Bill 375) passed in 2007 (ARB, n.d.). TOD has become a central platform of regional transportation plans and other planning documents, in regions with legacy transit systems like San Francisco Bay Area and New York City, and in regions with new transit development such as Sacramento and Los Angeles.

Planners have also promoted the social equity effects of transit and TOD. Lower-income households often have lower access to vehicles and are more reliant on transit. Hence, promoting subsidized or naturally-occurring affordable housing near transit as well as employment and retail opportunities could reduce transportation costs for lower-income households. This also produces a ready supply of transit riders which increases transit system efficiency.

However, the dual goals of environmental sustainability and social equity may run counter to each other. First, as the demand for living near transit increases, prices for TODresidences may increase without a commensurate increase in supply. This puts pressures on affordability near transit stations and may make subsidized housing development more expensive (Boarnet et al., 2017a). Second, since higher-income households drive more miles than lower-income households (Santos, McGuckin, Nakamoto, Gray, & Liss, 2009), they may reduce their vehicle-miles travelled (VMT) by a larger absolute amount when living near rail stations (CHPC & Transform, 2014). Empirically, two recent studies demonstrate this effect in Los Angeles and the San Francisco Bay Area, where households with incomes above $100,000 reduce VMT by over two times than of households within incomes below $50,000 when living within 0.5 miles of transit (Chatman, Xu, Park, & Spevack, 2017; Boarnet, Bostic, Rodnyansky, Santiago-Bartolomei, & Leslie, 2017b). Both these studies use household travel survey data and compare households living near transit to control households living further from transit.

Nevertheless, the extant literature has failed to address whether this tension between environmental sustainability and social equity holds true when considering GHG emissions, rather than VMT. Due to correlations between households' and their vehicles' characteristics, lower-income households may reduce their GHG emissions by a similar level as higher-income households when locating near transit, despite the fact that higher-income households reduce their VMT more.

Furthermore, what if transit stations and TODs are built in qualitatively different neighborhoods by income? Do differences in density or land use mix affect the VMT-income-transit access relationship? Previous studies have suggested that density, land use mix, and transit access all affect VMT (National Research Council, 2010) and the income-VMT relationship is also well established (*e.g.*, Santos et al., 2009). However, no previous studies have looked at the interrelationship of neighborhood type (via density and land use), income, transit access, and travel behavior.

An earlier iteration of our research (METRANS report 15-13) focused on the relationships between transit access, household income, and household VMT (which served as a proxy for GHG emissions) using data from the Los Angeles metropolitan area (Boarnet et al., 2017b). Notably, this work did not address the three gaps in the literature noted above, although we did introduce a land use typology for neighborhoods. In consideration of these facts, our current research builds on our earlier work by:

1. Incorporating a direct estimation of GHG using information on households' VMT, vehicle trips made, and vehicle technology;
2. Controlling for issues of residential self-selection by including measures of neighborhood land use consistent with the typology introduced in our earlier research;
3. Expanding the data analyzed to include the San Francisco Bay Area, Los Angeles, Sacramento, and San Diego metropolitan areas; and
4. Considering outcomes for transit system efficiency in addition to environmental sustainability goals.

Within this report, we compare four travel behavior outcomes (VMT, number of transit trips, share of trips that are made by transit, and the probability of taking a transit trip) between households living within and outside of 1 mile of a rail transit station pooled across four California metropolitan areas, controlling for household income and for neighborhood type. We also explore the relationship between VMT and GHG levels for households living within and outside of 0.5 miles of a rail transit station, controlling for household income and metropolitan area (rather than neighborhood type) (Boarnet et al., 2018). We believe exploring variations in the translation of household VMT to household GHG emissions at the metropolitan area level is a necessary first step before considering variations in the VMT-GHG relationship at the neighborhood-type level.

Using data from the 2010-2012 California Household Travel Survey (CHTS), three Tobit regressions and one logit regression are used to analyze the effect of income and transit access on travel behavior – including transit usage – controlling for neighborhood type. Primary findings indicate that higher income households reduce VMT when living near transit by more miles compared to lower-income households, regardless of neighborhood type. In contrast, lower-income households make more transit trips and increase transit mode share at higher rates than higher-income households, when living in denser, transit served neighborhood. Two additional Tobit regressions, controlling for metropolitan area rather than neighborhood type, use the same data to analyze the effect of income and transit access on GHG emissions. These two regressions suggest an imperfect translation of changes in household VMT to changes in household GHG emissions that varies by metropolitan area.

The remainder of this report lays out the research questions, data, methods, and presents and discusses the results. Afterwards, the report suggests crucial findings for planners in the future implementation of TOD, particularly regarding the relative impacts TOD may have on social equity, transit system efficiency, and environmental goals depending on neighborhood type.

2. Literature Review

Twenty-five years of scholarship has found significant relationships between income, transit access, built environment characteristics, and some aspects of travel behavior. A complete listing would be impossible here and several exhaustive and critical reviews already exist. Instead, we briefly remark on studies which find relationships specifically between our outcome measures – VMT, GHG emissions, number of transit trips, transit mode share, and probability of taking transit – and our key explanatory measures – transit access, income, and neighborhood type with its constituents parts: residential and employment density, land use intensity, and employment-housing mix.

Household income is associated with decreased VMT and increased transit mode share, trip frequency (Badoe and Miller, 2000; Ewing and Cervero, 2001; Pucher and Renne, 2003; Santos et al., 2009) and the probability of taking transit (Chen Gong, & Paaswell, 2008). Transit access and living in TODs generally increase the number of transit trips taken (Cervero and Gorham, 1995), increase transit mode share (Khattak & Rodriguez, 2005; Lin & Long, 2008), increase the probability of taking a transit trips (Arrington and Cervero, 2008; Chen et al., 2008), and decrease VMT (Cervero, 2007). However, regional context (Cervero and Gorham, 1995) and transit mode type (Kitamura, Mokhtarian, & Laidet, 1997) moderate these effects.

Neighborhood type has been found to affect transit mode share (Lin & Long, 2008), and traditional neighborhood design and higher-accessibility areas tend to decrease VMT (Khattak & Rodriguez, 2005; Krizek, 2003). Increases in residential densities and employment densities have been associated with decreases in VMT (Cervero and Murakami, 2010; Lin & Long, 2008) and other travel behaviors (Badoe and Miller, 2000; Ewing and Cervero, 2001). The balance of jobs and housing in an area also effects VMT (Bento, Cropper, Mobarak, & Vinha, 2005; Krizek, 2003).

Even the most careful studies find it difficult to pinpoint a specific policy or built environment characteristics that affects VMT or transit system usage in every case, but most find joint significance of a number of built environment measures (Brownstone, 2008). Moreover, while many studies find statistically significant relationships, magnitudes of necessary density increases, for example, make policy recommendations questionable (Brownstone, 2008). Additionally, few studies consider interactions between income, transit access, and neighborhood type. Only Chatman et al. (2017), CHPC & Transform (2014), and Boarnet et al. (2017b) note that VMT reduction from increased transit access is largest for higher-income households.

Regarding the link between household VMT and GHG emission levels, previous studies, while indicating that a large share of GHG emissions come from households' personal vehicles (Brown, Southworth, & Sarzynski, 2008; Ewing et al., 2007), have largely failed to consider how household income, household vehicle characteristics, and VMT and GHG emissions are related. Research by Brownstone and Golob (2009) does suggest, however, that households in more dense neighborhoods tend to have lower VMT and own more fuel-efficient vehicles than equal-income households in less dense neighborhoods.

This report addresses three gaps in the literature: (1) we study specific built environment types; (2) we test interactions between transit access, household including income, and neighborhood type; and (3) we empirically explore how household VMT levels translate to household GHG emission levels.

To address the first two gaps, we ask ***Research Question 1:*** how do the relationships between travel behavior (both VMT and transit usage), household income, and transit access inside and outside of 1 mile of rail transit (One-Mile Areas) vary by neighborhood type? We expect differences in relationships due to rail station siting, household sorting, the differential supply and type of residential units by neighborhood, and the different potential for residential development based on existing zoning and other land use controls. We hypothesize that neighborhood-type and land use variables will dampen the income effect on VMT reduction from living in transit access. In contrast, we expect that neighborhood types will amplify the income effect on the frequency, share, and probability of transit usage.

To address the third gap, we ask ***Research Question 2:*** how is the relationship between VMT, income, and transit access inside and outside of 0.5 miles of transit (Half-Mile Areas) different from the relationship between GHG emissions, income, and transit access? We hypothesize that cross-sectional differences in GHG emissions for households within and outside Half-Mile Areas are less related to income than differences in VMT are, as lower-income households may drive less environmentally-friendly vehicles but higher-income households reduce VMT more when living near transit.

3. Data

We address the two research questions by combining three data sources to measure the effects of income, neighborhood characteristics, household income, and transit access on daily VMT, transit trips, transit trip share, probability of making a transit trip. We incorporate two emissions data sources to compare daily VMT with daily GHG emissions. We undertake this research in 22 California counties making up four metropolitan areas.

3.1 Study Area

California's four largest metropolitan areas have developed or expanded their rail transit systems over the past 25 years. Los Angeles and the San Francisco Bay Area (Bay Area) are large polycentric regions, while San Diego and Sacramento are both growing, monocentric cities. Similar neighborhood types exist within each of these metropolitan areas. For our first research question, we pool observations across these regions to compare household travel behavior across neighborhood types. For our second research question, we instead compare households' VMT and GHG emission patterns across the four metropolitan areas. As stated above, we believe exploring variations in the translation of household VMT to household GHG emissions at the metropolitan area level is a necessary first step before considering variations in translation at the neighborhood type level.

The household data come from responses to the 2010-2012 California Household Travel Survey (CHTS) in 22 counties: Imperial, Los Angeles, Orange, Riverside, San Bernardino, Ventura (for Los Angeles); Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma (for Bay Area); El Dorado, Placer, Sacramento, Sutter, Yolo, and Yuba (for Sacramento) and San Diego County (Kunzmann, 2013).

3.2 Rail Transit Access Data

In this report, we compare treatment households in One-Mile Areas (within 1 mile of transit) to control households outside of One-Mile Areas to answer our first research question. While our 1-mile definition reflects a larger catchment area than some studies (Guerra, Cervero, & Tischler, 2012), unadjusted dependent variable means by income and by neighborhood type are largely similar to half-mile definitions. To answer our second research question regarding the VMT-GHG link, we utilize the more traditional catchment size of Half-Mile Areas (Guerra et al., 2012). Such a catchment size is possible in this second analysis because observations are in less granular categories than within the first analysis (joint income and metropolitan area categories are used versus the first question's joint income and neighborhood type categories). Finally, in the TOD context, we define transit access as well-served intra-city rail stations, which could (or do) support significant development and would be likeliest to change residents' travel behavior.

Accordingly, we include light-rail and subway modes, which are ideal for considering travel behavior changes given their high volume, frequent service, and intra-city orientation. Of California's 710 rail stations open in or before 2013, 310 fit our definitions of transit access, including the Los Angeles County Metropolitan Transportation Authority subway and light rail, San Diego Trolley light rail, Sacramento light rail, Bay Area Rapid Transit subway, and the Santa Clara Valley Transportation Authority light rail. Location data for stations in these transit systems were obtained from SCAG, SANDAG, and MTC directly and using a generalized transit feed specification (GTFS) file for Sacramento.

The 392 remaining stations are excluded due to specifics of their mode type and incompatibility with the TOD definition based on passenger volume, service frequency, number of stops, or destination type. For example, we exclude Amtrak stations because their inter-city nature reflects different travel behavior and hence a distinct set of development patterns. We also exclude commuter rail stations (Metrolink, Caltrain, San Diego Coaster, San Diego Sprinter, Altamont Express) because of their less frequent service and the prevalence of park-and-ride type stations, leading to different land uses. Cable cars, Muni stops (essentially streetcar stops), bus rapid transit, and other bus stations are also excluded from the rail transit treatment category.

3.3 Household Demographics, VMT, and Trips Data

Data on households, trips, and VMT were obtained from households sampled in the 2010-2012 CHTS in the 22-county study area (Kunzmann, 2013). CHTS data were combined with GIS-based rail station location data for the 310 treatment TOD stations and a nearest station was calculated for each household's residential address. Households within One-Mile Areas are treatment households for our first research question; households within Half-Mile Areas are treatment households for our second research question. The address distance was also used to compute the distance to the closest central business district, which served as a control for location within the metropolitan area. We developed income categories based on the income distribution of sample households; for example, insufficient data was available to develop distinct income categories above $100,000. CHTS data was used to generate additional household variables including household size, number of vehicles per household, and number of employed members of a household.

The 2010-2012 CHTS dataset contains information for 42,426 households in California. Three sample size restrictions were made to the data for the purposes of this analysis. First, 5,718 households were removed due to empty travel diary data. Second, a further 3,010 households were removed due to missing household income information. Third, another 10,164 households were removed as they fell outside the four metropolitan areas of study or were missing geographic location information. After these operations, the final observation counts by metropolitan area were: 12,362 households in Los Angeles; 7,923 households in the Bay Area; 1,899 households in Sacramento; and 1,350 households in San Diego, equating to 23,534 total observations.

To obtain estimates of VMT for the 23,534 households in the analysis, the trip length variable from the household travel diary data was used. Within the CHTS, households can report trips that are made across a wide variety of transportation modes. When estimating VMT for each household, lengths from trips made across three of these modes were considered: a household member driving a personal vehicle; a household member riding as a passenger in a personal vehicle; and a household member riding on (as driver or passenger) a motorcycle, scooter, or moped (Kunzmann, 2013). VMT for each household was estimated by aggregating trip lengths for all trips across the above three modes; trips by a second, third, or more members of a household in the same vehicle were excluded to avoid double counting. Households who provided travel diary data but did not report any trips across the three modes above were assigned a VMT of zero. The top 5% of households by VMT were excluded from analysis exploring the first research question as outliers.

The remaining three travel behavior variables of interest – number of transit trips, transit trip share, and probability of taking a transit trip – were obtained from the CHTS' trips and mode variables. Public transit trip modes include bus (local, rapid, express, commuter, inter-city), school bus, public shuttle, dial-a-ride / para-transit, subway, light-rail, trolley, cable car, streetcar, ferry and boat. This category excluded non-motorized modes (walk, bike, wheelchair, other) and private transit (taxi / livery, rental car / shuttle, private shuttle, airplane, airport shuttle, other). Trip count data aggregated by public transit modes yielded the daily household number of transit trips. Transit trip share was computed as the number of daily transit trips divided by total daily trips. Probability of taking transit is a binary variable with a value of 1 if the household took a transit trip and 0 otherwise.

3.4 Household GHG Emissions Data

We obtained cross-sectional data on households' vehicle characteristics from the same 2010-2012 CHTS (Kunzmann, 2013).

To develop a proxy measure for overall GHG emissions by vehicle, we used two data sources on carbon dioxide (CO_2) emissions. We focused on CO_2 emissions as they represent

82% of U.S. GHG emissions (EPA, 2017). We applied carbon dioxide (CO_2) emission rates provided by the California Air Resource Board's (ARB) EMFAC 2014 model to the gas and diesel vehicles in our dataset (ARB, 2015). At the same time, we applied the EPA's online Fueleconomy.gov CO_2 emission rates to the hybrid and electric vehicles in our dataset.

To calculate emission rates for gas and diesel vehicles in our dataset via the ARB EMFAC 2014 model, we obtained the following inputs from the 2010-2012 CHTS: fuel type, model year, vehicle category, and county of residence. We mapped CHTS vehicle categories[1] to the EMFAC 2014 model categories according to weight and type data (ARB, 2015; Boarnet, Wang, & Houston, 2017). We excluded the following observations:

- vehicles whose fuel type was not gas, diesel, hybrid, or electric, *e.g.*, biofuel vehicles, as only those first four fuel types had emission rates available (100 observations excluded);[2]
- vehicles missing a model year, who had a model year prior to 1972, or whose model year was unknown (687 observations excluded); and
- vehicles missing a category in the CHTS or falling in a category unable to be mapped to the EMFAC 2014 model – the latter includes recreational vehicles, mopeds, scooters, and motorcycles[3] (4,210 observations excluded).

After these exclusions, the dataset available for analyzing the link between household VMT and household GHG emissions was comprised of 28,932 vehicles operated by 19,616 households.

Using the CHTS data, we calculated the number of daily trips and total daily VMT attributable to each of the 28,932 vehicles (Kunzmann, 2013). For each gas and diesel vehicle,

[1] These CHTS categories were: sedans, SUVs, pickup trucks, coupes, convertibles, hatchbacks, wagons, minivans, and vans.
[2] The hybrid and electric vehicles are covered not by the EMFAC 2014 model but by the EPA's fueleconomy.gov model.
[3] Motorcycle VMT represents less than 1% of total household VMT in the dataset.

we then multiplied these trip and VMT data by the EMFAC 2014 model's emission rates, which vary across fuel type, model year, vehicle category, and county of residence.[4] We incorporated constant assumptions of vehicle speed (the "aggregated speed" option in the EMFAC 2014 model) and season of the year (the "annual" option in the EMFAC 2014 model). While both of these latter factors impact vehicles' emission rates, the 2010-2012 CHTS did not record the necessary data to differentiate measures across vehicles.

Regarding the multiplication of vehicle trip and VMT data by emission rates, the EMFAC model provides emission rates for two distinct stages of vehicle operation: (1) the initial ignition or starting of the vehicle (termed the "STREX" factor); and (2) the subsequent driving of the vehicle (termed the "RUNEX" factor). As a result, for each vehicle *j* we multiplied the number of daily trips made by the appropriate STREX factor and its daily VMT by the appropriate RUNEX factor (*see* Equation 1). Doing so provided us with an aggregate estimate of CO_2 emissions for each of the gas and diesel vehicles in our cleaned dataset.

Equation 1: Gasoline and Diesel Daily Emissions Calculation

$$Daily\ household\ emissions(grams\ CO_2)_i =$$

$$\sum_j [daily\ trips_j * CO_2STREX_j\left(\frac{grams}{trip}\right) + \ daily\ VMT_j * CO_2RUNEX_j]$$

As aforementioned, we utilized the EPA's fueleconomy.gov data to apply emission rates to hybrid and electric vehicles. The EPA's fueleconomy.gov rates capture vehicles' running CO_2 emission rates for hybrid vehicles (synonymous with the RUNEX factor mentioned above) and both running and upstream CO_2 emission rates for electric vehicles (combining both into a single rate). Similar to the EMFAC 2014 model, the EPA's fueleconomy.gov model uses fuel type,

[4] County of residence matters because humidity and temperature affect a vehicle's emissions. We assumed annual average relative humidity and temperature levels for each of the 22 counties, using data from the National Oceanic and Atmospheric Administration (NOAA) from 2012.

vehicle make, model year, and body type to generate emission rates for a given vehicle. As no emission rates in this model apply to starting the vehicle, for each vehicle j we simply multiplied its daily VMT by the appropriate emission rates (*see* Equation 2).

Equation 2: Hybrid and Electric Daily Emissions Calculation

$$Daily\ household\ emissions(grams\ CO_2)_i = \sum_j [daily\ VMT_j * CO_2\ daily\ emissions\ rate_j \left(\frac{grams}{mile}\right)]$$

To calculate the total CO_2 emissions for each household we summed the calculated emissions for each of the household's vehicles, which then served as a proxy for household GHG emissions. The top 1% of households in the distribution of VMT were excluded from our analyses of GHG emissions as outliers.[5]

3.5 Neighborhood Types and Land Use Variables

To assess the relationship of neighborhood characteristics to travel behavior and transit access, we developed five (5) neighborhood types that differed by land use intensity and the ratio of employment to population. The population and employment in the neighborhood within 0.5 miles of each household in the sample was obtained from the 2009-2013 American Community Survey (U.S. Census Bureau, 2013a) and Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics Data (LODES) (U.S. Census Bureau, 2013b) and spatially interpolated from census tracts which surround the household's address (see Supplemental Materials 1). For each household, we calculated a measure of "land use intensity"

[5] The outlier criterion differed in the two analyses, and we did not see anything that suggests the results are sensitive to the difference in outlier criterion.

by summing the total neighborhood population and employment; a "land use mix" variable was then calculated by dividing neighborhood employment by population.

Neighborhood types have been used in TOD planning to reflect context-specific approaches to development near transit stations (e.g., CTOD, 2010; RPA, 2017). In California, such typologies have been used in regional transportation planning by Los Angeles County and the Metropolitan Transportation Commission (Bay Area) (L.A. Metro, 2012; Reconnecting America, 2007). TOD planning categorizes neighborhoods by type to address density, development potential, walkability, and other planning considerations for station areas.

Our report extends this approach by assigning a neighborhood type to each treatment and control household based on their surrounding 0.5-mile radius environment. We divided each household's neighborhood into one of 5 types based on two criteria: (1) the area's land use intensity, and (2) its employment versus residential orientation. Reports from similar efforts in Los Angeles County and the Bay Area provided criteria cutoffs and resulting neighborhood types (see Table 1) (Boarnet et al., 2017b; CTOD, 2010; L.A. Metro, 2012; Reconnecting America, 2007). We limited the number of neighborhood types to five, so that we could maximize the number of households within each neighborhood type. We retained the same criteria cutoffs across our four metropolitan areas to ensure comparability. We note, however, that Los Angeles and the Bay Area have a higher proportion of households in the two denser neighborhood types, High Density Downtown and Central Place. During this determination of neighborhood types, 41 households were unable to be matched to a neighborhood type and were therefore excluded from analyses incorporating neighborhood type.

To reiterate, these neighborhood type variables were used to explore ***Research Question 1*** but not ***Research Question 2***, *i.e.*, we controlled for metropolitan area but not neighborhood type in exploring ***Research Question 2***. This is because we believe exploring the VMT – GHG relationship at the metropolitan level is necessary before delving into variations in the relationship at the more granular neighborhood type level.

Table 1: Neighborhood Type Criteria Cutoffs and Resulting Counts by Metropolitan Area
Source: author calculations on ACS 2009-2013, SCAG, SANDAG, MTC, SacRTD

Criteria → **Neighborhood Type**	**Employment mix** (ratio of workers to residents)	**Intensity** (population +employees)	**Bay Area**	**Los Angeles**	**Sacra-mento**	**San Diego**	**All Metros**
1. High Density Downtown	>1.5	>45,000	101	49	1	5	156
2. Central Place	<0.5	>21,000	977	1,042	42	56	2,117
	0.5-1.5	>12,000					
	>1.5	12,000-45,000					
3. Neighborhood Center	<0.5	12,000-21,000	1,716	2,873	322	247	5,158
	0.5-1.5	<12,000					
4. Single Family Home Area	>1.5	>45,000	4,983	8,138	1,506	1,017	15,644
5. Industrial \ Employment Center	>1.5	>45,000	145	223	28	22	418

4. Methods

4.1 Descriptive Statistics

This report concerns the joint effect of household income, neighborhood characteristics, and transit access on household travel behavior. It further addresses how changes in household VMT translate to changes in household GHG emissions, using VMT, vehicle trip, and vehicle technology data from the 2010-2012 CHTS (Kunzmann, 2013).

Travel behavior (VMT, transit trips, transit share, and probability of taking transit) of treatment households living within One-Mile Areas is compared to that of households living outside the One-Mile Areas; this comparison is made cross-sectionally and within the same time period. The descriptive statistics in Tables 2 and 3 show the breakdown of VMT and transit behavior, respectively, by rail transit access (within versus outside One-Mile Area), household income, and neighborhood type. These descriptive statistics are pooled across the four California metropolitan areas in our study.

Similarly, we compare changes in household GHG emissions to changes in household VMT by rail transit access (this time within versus outside Half-Mile Area), household income, and metropolitan area. Again, we are able to use the more traditional catchment size of Half-Mile Areas in this second analysis because the data are categorized across metropolitan areas instead of neighborhood types. These descriptive statistics are displayed in Table 4.

To explore our hypotheses we use a number of Tobit and logit regressions, which we describe in detail below. Before doing so, we note that the small number of observations in our dataset for the High Density Downtown (156 observations) and Industrial / Employment Center (418 observations) neighborhood types prevented us from running regressions that included these data.

4.2 Regression Specifications

4.2.1. Regression Specifications for Research Question 1

To explore ***Research Question 1***, *i.e.*, to estimate the joint effect of income and transit access on household travel behavior, we run independent regressions for the Central Place, Neighborhood Center, and Single Family Home Area neighborhoods pooled across the four metropolitan areas.

Our dependent variables include two continuous and one count measure of household travel behavior – VMT, number of transit trips, and percentage of total trips taken on transit – and one binary variable – the probability of taking at least one transit trip. The CHTS data are censored at 0 for the continuous and count dependent variables. More specifically, 7.5% of households in our cleaned dataset had a daily VMT of zero, 88% had zero transit trips, and 86% had a transit share of trips equal to zero. To account for this econometrically, we use a Tobit regression functional form to reduce the bias originating from censored variables (Min & Agresti, 2002) and a logit regression functional form for predicting the non-censored probability dependent variable.

The key explanatory factors in these regressions are rail transit access (within versus outside One-Mile Areas) and household income category[6], with a separate model run for each of the three neighborhood types, *i.e.*, Central Place, Neighborhood Center, and Single Family Home Area. For each household, we also control for the number of household vehicles, household size, the number of household members who are employed, and the household's distance to the nearest central business district (CBD) based on the pertinent travel behavior literature (National Research Council, 2010). Housing price information is not available for use as a control from the CHTS data. The equation below (Equation 3) describes the Tobit models used for the regressions by neighborhood type:

Equation 3: Daily VMT, transit trips, and transit share Tobit prediction model

$$Y_i \begin{cases} Y_i^* \text{ if } Y_i^* > 0 \\ 0 \text{ if } Y_i^* \leq 0 \end{cases}$$

[6] The 2010-2012 CHTS reports household income across ten categories (Kunzmann, 2013). Due to sample size restrictions, we collapsed these ten categories down to four: $0 - $25,000; $25,001 - $50,000; $50,001 - $100,000; and above $100,000.

Where for each neighborhood type, $Y_i^* = \beta_0 + \sum_{j=1}^{m} \beta_j W_{ij} + \sum_{k=1}^{n} \beta_k X_{ik} + \sum_{j=1}^{m} \sum_{k=1}^{n} \beta_{jk} W_{ij} X_{ik} + \sum_{l=1}^{p} \beta_q Z_i + distancetoCBD + \varepsilon_i$

The equation above shows a two-step process for each neighborhood type and income category model. Y_i* is a latent variable related to Y_i, which is the observed daily VMT, daily transit trips, and daily transit mode share for household *i* by the first equation, assuming a normal probability distribution for Y*. Then, depending on the regression, the latent variable is regressed on the following independent variables:

- W_{ij} = household income band dummy variables for income groups *j* ($0-$25,000; $25,001-$50,000; $50,001-$100,000; and >$100,000)
- X_{ik} = dummy variable for household living One Mile of a rail transit station
- $W_{ij}X_{ik}$ = income band dummy and one-mile rail dummy interaction terms
- Z_i = set of household characteristics: household size, number of household vehicles, and number of household members employed
- *Distance to CBD* = Euclidean distance to nearest central business district.

Equation 4 below shows the uncensored variable logit model for predicting that a household makes a transit trip by transit access and household income, with a separate model run for each neighborhood type (Cameron & Trivedi, 2005):

Equation 4: Probability of taking a transit trip Logit prediction model

The probability of a household *i* taking a transit trip is $Y_i \begin{cases} 1 \text{ with probability p} \\ 0 \; with \; probability \; 1-p \end{cases}$

Where $p = \Lambda(\boldsymbol{x}'\beta) = \frac{e^{x'\beta}}{1+e^{x'\beta}}$, $\Lambda(.)$ is the logistic cumulative distribution function. The odds-ratio of the logit is $\frac{p}{1-p} = e^{x'\beta}$.

Where for each neighborhood type, $\boldsymbol{x}'\beta = \beta_0 + \sum_{j=1}^{m} \beta_j W_{ij} + \sum_{k=1}^{n} \beta_k X_{ik} + \sum_{j=1}^{m} \sum_{k=1}^{n} \beta_{jk} W_{ij} X_{ik} + \sum_{l=1}^{p} \beta_q Z_i + distancetoCBD + \varepsilon_i$

Interaction variables between income strata and living within One-Mile Areas enable comparisons of travel behavior estimates within each neighborhood type, inside and outside of TOD by income group. Due to outliers in sampled VMT, the VMT Tobit models exclude households in the top 5% of VMT. Analyzing the inter-quartile range of the VMT distribution for the pooled sample as well as by metropolitan area confirmed this approach for removing outliers.

The above regressions were used to predict dependent variable levels and probabilities for households across the transit behaviors included in our analysis. Predicted values were based on the regression models' estimated parameters and the households' characteristics observed in the CHTS. It is possible to obtain predicted values via Tobit modeling in various ways (Amemiya, 1984). For this analysis, travel behavior values are always greater than or equal to zero, so we generate expected values for households by fitting them to a distribution whose minimum value is zero; maximum predicted values were not specified for this distribution (synonymous with the "ystar(0, .)" prediction option in Stata). As with the Tobit regressions, households in the top 5% of VMT were excluded when predicting VMT, number of transit trips made, and transit modal share of trips. For the logit regression of probability a household makes a daily transit trip, predicted probabilities of making a daily transit trip were generated using Stata's predict function.

4.2.2. Regression Specifications for Research Question 2

To explore ***Research Question 2***, *i.e.*, to estimate the joint effect of income and transit access on household VMT and separately on household GHG emissions, we run independent regressions each of the four metropolitan areas.

Our dependent variables are two continuous variables: household VMT and directly-calculated household GHG emissions. As discussed in the prior section, the VMT data are censored at 0 – this is true for GHG emission as well. Again, to account for this econometrically, we use a Tobit regression functional form to reduce the bias originating from censored variables.

The key explanatory factors in these regressions are rail transit access (for the Bay Area and Los Angeles areas, within versus outside Half-Mile Areas; for Sacramento and San Diego areas, Euclidean distance to the nearest rail transit station)[7] and household income category. For each household, we also control for the number of household vehicles, household size, and the number of household members who are employed. The equation below (Equation 5) describes the Tobit models used for these VMT and GHG regressions:

Equation 5: Daily VMT and daily GHG emissions Tobit prediction model

$$Y_i \begin{cases} Y_i^* \text{ if } Y_i^* > 0 \\ 0 \text{ if } Y_i^* \leq 0 \end{cases}$$

Where for each neighborhood type, $Y_i^* = \beta_0 + \sum_{j=1}^{m} \beta_j W_{ij} + \sum_{k=1}^{n} \beta_k X_{ik} + \sum_{j=1}^{m} \sum_{k=1}^{n} \beta_{jk} W_{ij} X_{ik} + \sum_{l=1}^{p} \beta_q Z_i + \varepsilon_i$

Depending on the regression, the latent variable (VMT or GHG emissions) is regressed on the independent variables:

[7] Euclidean distance to nearest rail transit station had to be used in the regression models for Sacramento and San Diego due to the CHTS' insufficient sample sizes of households in these metropolitan areas living within a half mile of rail transit.

- W_{ij} = household income band dummy variables for income groups *j* ($0-$25,000; $25,001-$50,000; $50,001-$100,000; and >$100,000)
- X_{ik} = dummy variable for household living within a Half-Mile Area of a rail transit station (if metropolitan area is the Bay Area or Los Angeles), *or* continuous variable measuring Euclidean distance of household to nearest rail transit station (if metropolitan area is Sacramento or San Diego)
- $W_{ij}X_{ik}$ = income band dummy and rail access variable (dummy or continuous) interaction terms
- Z_i = set of household characteristics: household size, number of household vehicles, and number of household members employed.

The interaction terms between income band dummies and rail access variables allow us to identify metropolitan area-specific joint effects on VMT and GHG emissions; we categorize our predicted values by income band and inside versus outside Half Mile Area. We do so for Sacramento and San Diego in addition to the Bay Area and Los Angeles metropolitan areas. In our Tobit regression analyses we exclude the top 1% of households in terms of VMT.

As with the first set of regressions, these models were used to predict dependent variable levels for households in our dataset. Predicted values were based on the regression models' estimated parameters and the households' characteristics observed in the CHTS. We leveraged the same method of predicting values from a Tobit model for this second set of regressions.

5. Results

5.1 Descriptive Statistics

5.1.1. Descriptive Statistics for Research Question 1

This section compares sample averages by income category and neighborhood type as well as differences between treatment and control households. Average unadjusted household VMT increases with income regardless of transit access (Table 2), in line with prior findings (Brownstone & Golob, 2009; Cervero & Kockelman, 1997; Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002). Yet, higher-income households who live within 1 mile of rail show a larger VMT difference than lower-income households, similar to Chatman et al. (2017) and Boarnet et al. (2017b). Similarly, households in lower density neighborhoods have higher unadjusted daily VMT (Table 2), in line with Ewing and Cervero (2001) and Cervero and Kockelman (1997). When combining sample averages between incomes and neighborhood types, it appears that lowest-income households reduce VMT most in higher-density areas, and highest-income households reduce VMT most in lower-density areas (Table 2). This heterogeneity reflects the need to control for both income and neighborhood type in assessing effects on VMT.

Trip-related travel behavior is also related to income and neighborhood type. While total trip amounts are similar by household, the unadjusted mean number of transit trips taken is highest for households with incomes below $25,000 and by those living in denser neighborhoods (Table 3). These patterns persist within and outside of one mile of rail transit. The probability of making any transit trips also increases with density and decreases with income, patterns which persist in and outside of transit proximity. Average unadjusted household transit mode share is also sensitive to income and neighborhood context. Lowest-income households have the highest transit share both inside and outside 1 mile of transit (Table 2). Central Place neighborhood residents have the highest transit mode share further and nearer to rail access (Table 2). These trip behavior statistics are consistent with the prior literature (National Research Council, 2010).

5.1.2. Descriptive Statistics for Research Question 2

Turning to ***Research Question 2*** and its analysis by metropolitan area, average VMT by household income rises for households living inside Half Mile Areas as well as households living outside Half Mile Areas for all four metropolitan areas (*see* Table 4). While VMT rises with income in each of these sub-groups, holding income constant, households within Half Mile Areas have lower VMT on average compared to households outside Half Mile Areas. This finding reaffirms research on the connection between VMT, income, and rail transit access (Holtzclaw et al., 2002; Kain & Fauth, 1976; Zegras, 2010). It also aligns with the VMT trends for "all neighborhood types" inside and outside One Mile Areas shown in Table 2.

Similar to the VMT figures for Half Mile Areas listed in Table 4, the household GHG emissions listed in Table 5 appear to depend on the California metropolitan area. Again similar to VMT, controlling for income, households living within Half Mile Areas have lower GHG emissions on average compared to households living outside Half Mile Areas. Unlike the trends shown in Table 4, the relationship between income and GHG emissions is less clear. For example, in the Bay Area, households earning $50,001-$100,000 and living within Half Mile Areas have lower GHG emissions on average than households earning $25,001-$50,000 and living within Half Mile Areas (*see* Table 5). This likely reflects the fact that wealthier households have higher VMT on average but that poorer households drive older vehicles on average (*see* Table 6) and are less likely to own hybrid or electric vehicles; together, these descriptive statistics suggest an imperfect translation of VMT to GHG emissions by household income and rail transit access due to a vehicle technology effect.

Table 2: Descriptive Statistics of Average Vehicle Miles Traveled (VMT) by Income Category, Neighborhood Type, and Rail Transit Access, across 4 California Metropolitan Areas
Note: VMT sample excludes top 5% of VMT observations
Source: California Household Travel Survey 2010-2012, U.S. Census 2010

		Mean VMT (Miles)					Sample Size (Households)				
Rail Station Access	**Neighborhood Type**	**Less than $25,000**	**$25,000 - $49,999**	**$50,000 - $99,999**	**$100,000 +**	**All Incomes**	**Less than $25,000**	**$25,000 - $49,999**	**$50,000 - $99,999**	**$100,000 +**	**All Incomes**
Outside of 1 mile	High Density Downtown	-	35.2	31.9	22.6	27.4	0	2	6	9	17
	Central Place	20.8	21.5	28.9	37.1	29.5	153	189	373	404	1119
	Neighborhood Center	21.6	30.5	37.6	48.3	37.1	646	809	1285	1289	4029
	Single Family Home Area	28.3	36.2	45.9	54	45.4	1483	2374	4662	5243	13762
	Industrial/Empl. Center	19.5	26.9	46	46.8	40.4	39	51	112	134	336
	All Neighborhood Types	25.8	33.9	43.2	51.8	42.6	2321	3425	6438	7079	19263
Within 1 mile	High Density Downtown	6	10.1	13.4	28.6	16	31	17	47	42	137
	Central Place	10.7	18.7	25.3	27.3	21	231	199	258	270	958
	Neighborhood Center	19.3	25.9	31.1	39.9	29.6	232	191	258	264	945
	Single Family Home Area	22.8	31.8	40.7	43.9	37.6	132	180	324	316	952
	Industrial/Empl. Center	25.7	18.7	39.2	39.2	35.7	3	9	23	29	64
	All Neighborhood Types	16.3	24.7	32.2	37.1	28.9	629	596	910	921	3056
Difference (within minus outside)	High Density Downtown	-	-25.2	-18.5	6	-11.4					
	Central Place	-10.1	-2.8	-3.6	-9.8	-8.5					
	Neighborhood Center	-2.3	-4.6	-6.6	-8.4	-7.4					
	Single Family Home Area	-5.5	-4.4	-5.2	-10.1	-7.8					
	Industrial/Empl. Center	6.2	-8.2	-6.8	-7.6	-4.7					
	All Neighborhood Types	-9.5	-9.2	-11.1	-14.8	-13.7					

Table 3: Descriptive Statistics of Trips by Income Category, Neighborhood Type, and Rail Transit Access, across 4 California Metropolitan Areas
Source: California Household Travel Survey 2010-2012, U.S. Census 2010

		Neighborhood Type					Income Category			
Variable	**Rail Station Access**	**High Density Downtown**	**Central Place**	**Neighborhood Center**	**Single Family Home Area**	**Industrial/Empl. Center**	**Less than $25,000**	**$25,000 - $49,999**	**$50,000 - $99,999**	**$100,000 +**
Mean Trips per Household	>1 mile	5.1	6.5	5.9	5.5	5.5	5.4	5.2	5.4	6.1
	<1 mile	7.5	7.3	7	6.5	5.2	6.8	6.3	6.7	7.7
	Difference (near – far)	2.3	0.9	1.1	1	-0.3	1.4	1	1.2	1.6
Mean Vehicle Trips per Household	>1 mile	3.2	3.6	4.1	4.4	4.4	3.1	3.9	4.4	4.8
	<1 mile	1.7	2.6	3.8	4.3	3.9	2.1	3.3	3.8	4.3
	Difference (near – far)	-1.5	-1	-0.4	-0.1	-0.5	-1	-0.6	-0.6	-0.5
Mean Transit Trips per Household	>1 mile	0.9	0.8	0.4	0.2	0.2	0.6	0.3	0.2	0.2
	<1 mile	1.3	1.1	1.1	0.6	0.8	1.5	0.8	0.7	0.7
	Difference (near – far)	0.4	0.3	0.6	0.4	0.6	0.8	0.5	0.5	0.4
Mean Walk/Bike/Other Trips per Household	>1 mile	1.6	2.3	1.4	0.9	0.9	1.7	1	0.9	1.1
	<1 mile	4.6	3.6	2.3	1.7	0.9	3.2	2.2	2.2	2.8
	Difference (near – far)	3	1.3	0.9	0.8	0	1.5	1.2	1.4	1.6
Probability of Taking a Vehicle Trip	>1 mile	71%	81%	89%	94%	93%	73%	90%	95%	97%
	<1 mile	42%	62%	81%	89%	91%	50%	75%	84%	87%
	Difference (near – far)	-29%	-19%	-8%	-5%	-2%	-23%	-16%	-12%	-10%
Probability of Taking a Transit Trip	>1 mile	12%	20%	13%	8%	8%	20%	10%	7%	9%
	<1 mile	41%	37%	26%	19%	10%	40%	25%	23%	25%
	Difference (near – far)	29%	17%	14%	10%	2%	20%	15%	16%	16%
Probability of Taking a Walk/Bike/Other Trip	>1 mile	53%	52%	38%	28%	29%	43%	30%	27%	33%
	<1 mile	80%	69%	49%	42%	19%	65%	51%	46%	55%
	Difference (near – far)	27%	17%	12%	13%	-10%	22%	21%	20%	22%
Transit Trip Share	>1 mile	8%	5%	4%	2%	2%	7%	3%	2%	2%
	<1 mile	12%	11%	8%	5%	5%	15%	8%	6%	6%
	Difference (near – far)	4%	6%	4%	3%	1%	8%	5%	4%	4%
Trips Sample Size	outside 1 mile	17	1146	4180	14663	351	2389	3554	6791	7623
	within 1 mile	139	971	978	981	67	632	610	937	957

Table 4: Descriptive Statistics of Average Vehicle Miles Traveled (VMT) by Income Category and Rail Transit Access (Half Mile Area Indicator), across 4 California Metropolitan Areas
Note: VMT sample excludes top 1% of VMT observations
Source: California Household Travel Survey 2010-2012

San Francisco Bay Area	**Average Actual VMT**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in VMT *(Within minus outside)***
$0-$25,000	26.07	13.6	560	88	-12.47
$25,001-$50,000	34.89	24.83	1,043	101	-10.07
$50,001-$100,000	44.87	21.78	2,238	191	-23.09
>$100,000	56.54	37.49	3,379	244	-19.05
All income levels	47.43	27.26	7,220	624	-20.17

Los Angeles	**Average Actual VMT**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in VMT *(Within minus outside)***
$0-$25,000	30.05	14.32	1,809	148	-15.73
$25,001-$50,000	40.28	25.76	2,261	121	-14.52
$50,001-$100,000	51.76	36.39	3,920	128	-15.37
>$100,000	61.09	55.31	3,790	62	-5.78
All income levels	49.22	29.03	11,780	459	-20.2

Sacramento	**Average Actual VMT**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in VMT *(Within minus outside)***
$0-$25,000	31.21	18.68	201	13	-12.53
$25,001-$50,000	41.26	25.98	356	17	-15.28
$50,001-$100,000	53.38	70.58	727	21	17.19
>$100,000	65.38	66.39	529	17	1.02
All income levels	52.04	48.46	1,813	68	-3.58

San Diego	**Average Actual VMT**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in VMT *(Within minus outside)***
$0-$25,000	21.47	15.21	166	29	-6.25
$25,001-$50,000	34.6	32.51	231	14	-2.08
$50,001-$100,000	51.24	50.98	425	19	-0.26
>$100,000	67.7	41.93	436	17	-25.77
All income levels	49.96	32.63	1,258	79	-17.33

Table 5: Descriptive Statistics of Average GHG Emissions (grams) by Income Category and Rail Transit Access (Half Mile Area Indicator), across 4 California Metropolitan Areas
Note: GHG emissions sample excludes top 1% of VMT observations
Source: California Household Travel Survey 2010-2012, EMFAC 2014 and fueleconomy.gov models

San Francisco Bay Area	Average Actual GHG		Sample Size		
	Non-TOD	TOD	Non-TOD	TOD	Difference in GHG *(Within minus outside)*
$0-$25,000	13,471	13,254	345	27	-217
$25,001-$50,000	14,743	13,492	839	58	-1,250
$50,001-$100,000	18,412	11,059	1,962	124	-7,352
>$100,000	20,322	15,710	3,015	178	-4,611
All income levels	18,570	13,716	6,161	387	-4,854

Los Angeles	Average Actual GHG		Sample Size		
	Non-TOD	TOD	Non-TOD	TOD	Difference in GHG *(Within minus outside)*
$0-$25,000	13,620	10,802	1,090	54	-2,818
$25,001-$50,000	15,122	14,146	1,906	78	-976
$50,001-$100,000	18,728	15,782	3,503	104	-2,945
>$100,000	21,254	24,423	3,396	52	3,169
All income levels	18,337	15,965	9,895	288	-2,372

Sacramento	Average Actual GHG		Sample Size		
	Non-TOD	TOD	Non-TOD	TOD	Difference in GHG *(Within minus outside)*
$0-$25,000	12,525	8,523	129	8	-4,002
$25,001-$50,000	15,625	9,730	298	15	-5,894
$50,001-$100,000	19,915	23,094	638	13	3,179
>$100,000	22,095	29,656	459	16	7,561
All income levels	19,107	19,017	1,524	52	-91

San Diego	Average Actual GHG		Sample Size		
	Non-TOD	TOD	Non-TOD	TOD	Difference in GHG *(Within minus outside)*
$0-$25,000	12,678	8,627	105	11	-4,051
$25,001-$50,000	15,413	16,867	196	8	1,455
$50,001-$100,000	21,473	19,438	379	14	-2,035
>$100,000	24,105	19,356	385	15	-4,749
All income levels	20,442	16,506	1,065	48	-3,936

Table 6: Descriptive Statistics of Vehicle Model Year by Income Category and Rail Transit Access (Half Mile Area Indicator), across 4 California Metropolitan Areas
Source: California Household Travel Survey 2010-2012

San Francisco Bay Area	**Average Model Year**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in Vintage *(Within minus outside)***
$0-$25,000	2000	1999	404	32	1.30
$25,001-$50,000	2001	2000	1,055	75	1.70
$50,001-$100,000	2003	2003	2,833	143	0.40
>$100,000	2004	2003	4,995	255	0.90
All income levels	2003	2002	9,287	505	1.10

Los Angeles	**Average Model Year**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in Vintage *(Within minus outside)***
$0-$25,000	2001	1998	1,324	60	2.2
$25,001-$50,000	2002	2002	2,510	96	0.2
$50,001-$100,000	2004	2003	5,233	146	1.0
>$100,000	2005	2005	5,704	79	0.2
All income levels	2004	2002	14,771	381	1.4

Sacramento	**Average Model Year**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in Vintage *(Within minus outside)***
$0-$25,000	1999	1998	150	9	1.6
$25,001-$50,000	2002	2004	379	15	-1.7
$50,001-$100,000	2003	2002	913	25	1.4
>$100,000	2005	2004	753	26	1.3
All income levels	2003	2002	2,195	75	1.0

San Diego	**Average Model Year**		**Sample Size**		
	Non-TOD	**TOD**	**Non-TOD**	**TOD**	**Difference in Vintage *(Within minus outside)***
$0-$25,000	2000	2002	125	12	-2.3
$25,001-$50,000	2002	2001	249	12	1.1
$50,001-$100,000	2003	2006	576	19	-3.3
>$100,000	2005	2005	703	22	0.4
All income levels	2004	2004	1,653	65	-0.5

5.2 Regression Results

5.2.1. Regression Results for Research Question 1

Regression results show a statistically significant relationship between all four travel behavior outcome variables and transit access and income for the Neighborhood Center and Single Family Home Area neighborhood types (*see* Tables 7, 8, 9, 10). In contrast, in Central Place neighborhoods, there is a weaker but statistically significant association with VMT and transit access and a weaker association with income and VMT and income and number of transit trips. Interaction variables are significant for transit access and income below $25,000 in Neighborhood Centers and transit access and income between $25,000 and $50,000 for Single Family Home Areas on the number of transit trips per household and on transit trip mode share. Similarly, the interaction term between transit access and income below $25,000 is significant in Neighborhood Centers and Single Family Home Areas and between transit access and income between $25,000 and $50,000 in Single Family Home Areas on the odds of taking a transit trip. In addition, joint significance tests indicate that each neighborhood's explanatory variables are jointly significant in their effects on all of the travel behavior outcomes.

5.2.2. Predicted Values from Regression Results for Research Question 1

This section shows differences in predicted values between travel behavior outcomes within and outside of One Mile Areas.

All households groups living proximate to transit are predicted to decrease VMT compared to those who live far from transit. More importantly, households with incomes over $100,000 living within One Mile Areas show the highest predicted VMT decreases, regardless of neighborhood type (Table 11). These differences are statistically larger than any other

Table 7: Results for VMT Tobit Regressions, for 3 Neighborhood Types, pooled across 4 California metropolitan areas
Note: Sample excludes top 5% of VMT observations
Source: California Household Travel Survey 2010-2012

	Central Place	Neighborhood Center	Single Family Home Area
Household Lives within 1 Mile of Rail Station	-4.751^	-4.711*	-7.759***
	(-1.69)	(-2.01)	(-3.57)
Income <$25K	-6.546+	-16.68***	-14.94***
	(-1.82)	(-9.07)	(-12.36)
Income 25K-50K	-8.965**	-9.221***	-9.242***
	(-2.81)	(-5.76)	(-9.53)
Income 50K-100K	-1.972	-6.428***	-3.697***
	(-0.78)	(-4.72)	(-4.85)
Within 1 mile * Income <$25K	-4.193	4.913	2.202
	(-0.87)	(1.37)	(0.53)
Within 1 mile * Income 25K-50K	5.570	1.603	2.469
	(1.21)	(0.44)	(0.68)
Within 1 mile * Income 50K-100K	5.770	1.703	4.545
	(1.45)	(0.52)	(1.50)
Household Size	2.575***	1.847***	3.033***
	(3.53)	(4.62)	(11.74)
Number of Vehicles in Household	18.26***	10.60***	6.966***
	(15.53)	(16.62)	(17.31)
Number of Employed Household Members	-0.545	5.111***	6.798***
	(-0.43)	(7.26)	(15.89)
Distance to Nearest Central Business District	0.168*	0.104***	0.0587***
	(1.97)	(3.71)	(4.12)
Constant	-5.641+	8.736***	15.63***
	(-1.93)	(4.87)	(14.14)
Sigma Constant	34.19***	33.91***	37.01***
	(54.84)	(93.23)	(166.29)
N	2077	4974	14714
Log-Likelihood	-8214	-22520	-71260
F-Statistic	53.53***	111.26***	237.34***
Prob>F	0.000	0.000	0.000

*Dependent variable: VMT. Omitted category: income >$100,000. t-statistics in parentheses, other than for Sigma, where standard error is in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1.*

Table 8: Results for Number of Transit Trips Tobit Regressions, for 3 Neighborhood Types, pooled across 4 California metropolitan areas
Note: Sample excludes top 5% of VMT observations
Source: California Household Travel Survey 2010-2012

	Central Place	**Neighborhood Center**	**Single Family Home Area**
Household Lives within 1 Mile of Rail Station	0.647	1.547***	2.075***
	(1.59)	(3.63)	(5.19)
Income <$25K	0.936+	1.406***	1.210***
	(1.83)	(3.98)	(4.62)
Income 25K-50K	0.155	-0.199	0.00130
	(0.31)	(-0.57)	(0.01)
Income 50K-100K	-0.421	-0.425	-0.578**
	(-1.01)	(-1.36)	(-3.02)
Within 1 mile * Income <$25K	-0.625	-0.978+	-1.115
	(-0.99)	(-1.66)	(-1.57)
Within 1 mile * Income 25K-50K	-0.147	-0.891	-1.585*
	(-0.22)	(-1.34)	(-2.26)
Within 1 mile * Income 50K-100K	0.274	0.424	-0.860
	(0.47)	(0.71)	(-1.44)
Household Size	0.870***	0.902***	1.007***
	(8.46)	(11.88)	(17.13)
Number of Vehicles in Household	-2.629***	-2.411***	-2.132***
	(-14.35)	(-15.99)	(-18.96)
Number of Employed Household Members	0.949***	1.073***	1.020***
	(5.16)	(7.30)	(9.88)
Distance to Nearest Central Business District	-0.101***	-0.0500***	-0.0326***
	(-5.90)	(-7.02)	(-8.78)
Constant	-1.855***	-4.189***	-6.226***
	(-4.24)	(-10.45)	(-20.38)
Sigma Constant	3.863***	4.454***	4.941***
	(29.76)	(33.36)	(42.89)
N	2117	5158	15644
Log-Likelihood **F-Statistic** **Prob>F**	-2212 32.13*** 0.000	-3408 48.58*** 0.000	-6848 64.16*** 0.000

*Dependent variable: Number of Transit Trips. Omitted category: income >$100,000. t-statistics in parentheses, other than for Sigma, where standard error is in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1.*

Table 9: Results for Transit Trip Mode Share Tobit Regressions, for 3 Neighborhood Types, pooled across 4 California metropolitan areas
Note: Sample excludes top 5% of VMT observations
Source: California Household Travel Survey 2010-2012

	Central Place	**Neighborhood Center**	**Single Family Home Area**
Household Lives within 1 Mile of Rail Station	0.0442	0.130***	0.198***
	(1.30)	(3.33)	(5.12)
Income <$25K	0.0700	0.148***	0.133***
	(1.64)	(4.62)	(5.31)
Income 25K-50K	0.00338	-0.0207	-0.00233
	(0.08)	(-0.66)	(-0.10)
Income 50K-100K	-0.0433	-0.0355	-0.0568**
	(-1.24)	(-1.26)	(-3.09)
Within 1 mile * Income <$25K	-0.00254	-0.0916+	-0.107
	(-0.05)	(-1.69)	(-1.56)
Within 1 mile * Income 25K-50K	0.0187	-0.0715	-0.139*
	(0.34)	(-1.18)	(-2.06)
Within 1 mile * Income 50K-100K	0.0370	0.0319	-0.0853
	(0.75)	(0.58)	(-1.47)
Household Size	0.0614***	0.0745***	0.0933***
	(7.09)	(10.73)	(16.48)
Number of Vehicles in Household	-0.222***	-0.222***	-0.210***
	(-14.39)	(-16.07)	(-19.20)
Number of Employed Household Members	0.0706***	0.0879***	0.0894***
	(4.56)	(6.56)	(8.99)
Distance to Nearest Central Business District	-0.00798***	-0.00431***	-0.00274***
	(-5.63)	(-6.73)	(-7.76)
Constant	-0.103**	-0.338***	-0.573***
	(-2.82)	(-9.28)	(-19.45)
Sigma Constant	0.325***	0.406***	0.475***
	(29.18)	(32.87)	(42.36)
N	2085	5073	15445
Log-Likelihood	-770	-1522	-3608
F-Statistic	32.41***	46.93***	62.75***
Prob>F	0.000	0.000	0.000

*Dependent variable: Transit Trip Mode Share. Omitted category: income >$100,000. t-statistics in parentheses, other than for Sigma, where standard error is in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1.*

Table 10: Results for Probability of Taking a Transit Trip Logit Regressions, for 3 Neighborhood Types, pooled across 4 California metropolitan areas. Coefficients reported as odds ratios
Note: Sample excludes top 5% of VMT observations
Source: California Household Travel Survey 2010-2012

	Central Place	**Neighborhood Center**	**Single Family Home Area**
Household Lives within 1 Mile of Rail Station	1.303	1.854***	2.311***
	(1.26)	(3.35)	(5.41)
Income <$25K	1.321	1.603**	1.516***
	(1.11)	(3.12)	(4.17)
Income 25K-50K	0.901	0.820	0.978
	(-0.42)	(-1.32)	(-0.24)
Income 50K-100K	0.724	0.800	0.787**
	(-1.60)	(-1.61)	(-3.01)
Within 1 mile * Income <$25K	0.774	0.585*	0.566*
	(-0.82)	(-2.13)	(-2.11)
Within 1 mile * Income 25K-50K	1.038	0.664	0.501*
	(0.11)	(-1.43)	(-2.51)
Within 1 mile * Income 50K-100K	1.233	1.127	0.683
	(0.74)	(0.47)	(-1.62)
Household Size	1.502***	1.443***	1.490***
	(7.65)	(11.26)	(19.04)
Number of Vehicles in Household	0.274***	0.325***	0.402***
	(-12.03)	(-13.51)	(-16.88)
Number of Employed Household Members	1.551***	1.660***	1.507***
	(4.63)	(7.48)	(9.41)
Distance to Nearest Central Business District	0.949***	0.977***	0.987***
	(-3.83)	(-5.77)	(-7.66)
Constant	0.527**	0.242***	0.125***
	0.117	0.041	0.014
N	2117	5158	15644
Log-Likelihood	-1026	-1815	-4162
Chi-Square Statistic	265.27***	481.43***	911.27***
Prob>Chi-Square	0.000	0.000	0.000
Pseudo-R^2	0.178	0.177	0.112

*Dependent variable: Probability of Taking a Transit Trip. Omitted category: income >$100,000. t-statistics in parentheses, other than for Sigma, where standard error is in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1.*

Table 11: Predicted Differences for Travel Behavior Variable Regressions between Households Residing within One Mile Areas minus outside One Mile Areas, for 3 Most Common Neighborhood Typologies in 4 California metropolitan areas
Source: California Household Travel Survey 2010-2012, U.S. Census 2010

Predicted VMT (Treatment minus Control)			
Income Level	Central Place	Neighborhood Center	Single Family Home Area
<$25,000	-13.7	-5.4	-8
$25,000-$50,000	-7.1	-6.8	-6.4
$50,000-$100,000	-9.5	-8.8	-7.4
>$100,000	-14.4	-10.9	-11.7
All Incomes	-13.2	-10.5	-10.8
Predicted Number of Transit Trips (Treatment minus Control)			
Income Level	Central Place	Neighborhood Center	Single Family Home Area
<$25,000	0.84	0.7	0.52
$25,000-$50,000	0.66	0.4	0.26
$50,000-$100,000	0.53	0.57	0.26
>$100,000	0.52	0.53	0.49
All Incomes	0.65	0.59	0.41
Transit Mode Share Predicted Values (Treatment minus Control)			
Income Level	Central Place	Neighborhood Center	Single Family Home Area
<$25,000	9.20%	6.40%	5.30%
$25,000-$50,000	6.20%	3.60%	2.60%
$50,000-$100,000	4.70%	5.00%	2.45
>$100,000	4.20%	4.60%	4.60%
All Incomes	6.00%	5.30%	4.00%
Transit Mode Share Predicted Values (Treatment minus Control)			
Income Level	Central Place	Neighborhood Center	Single Family Home Area
<$25,000	24%	16%	13%
$25,000-$50,000	21%	12%	8%
$50,000-$100,000	18%	17%	9%
>$100,000	17%	17%	16%
All Incomes	21%	17%	12%

income group in any neighborhood type excepts lowest-income households in Central Place neighborhoods. Moreover, in Neighborhood Center neighborhoods, this extends to households with incomes above $50,000. These findings signify that on an absolute level, the highest VMT reduction potential comes from high income households regardless of neighborhood sorting or land use conditions.

In contrast to VMT, households with incomes below $25,000 living within One Mile Areas show the highest predicted increase in the number of transit trips taken, in each neighborhood type, but differences are only statistically significant in Central Place neighborhoods (Table 11). Here too, all households living close to transit are predicted to increase the number of trips taken, but income seems less of a factor than in the VMT model. In addition, effect magnitudes are small – transit access increases the number of transit trips by 0.4-0.7 trips on average, and in no category by more than 0.85 daily trips.

Results on transit mode share largely follow those on transit trips (Table 4). As would be intuitively expected, households of all incomes increase transit as a mode share when living closer to rail stations. Lowest-income households do so to a greater extent in both Central Place and Neighborhood Center areas. Magnitudes of mode share shift toward transit average from 4-6% with over 9% for lowest-income households in the densest neighborhoods. Perhaps the combination of mode share shift and an increase in transit trips is a better indicator of increased transit system usage than either statistics individually.

Finally, proximity to transit increases the predicted probability of taking even a single transit trip for all households in each neighborhood type (Table 11). Each neighborhood has its pattern by income. In Central Places, the transit-access related increase in the probability of taking transit is inversely proportional to income for all incomes. In Neighborhood Centers, the increase in probability of taking transit is uniform across both higher and lower-income households. In Single Family Home Areas, lowest and highest-income households show highest magnitude increases in probability of transit usage. Average increases range from 12% to 21%.

Several patterns emerge when examining all the travel behavior outcomes together, in terms of the effect of transit access. First, VMT reduction through transit access is directly proportional with income across neighborhoods. Second, increases in transit system usage are inversely proportional with income in most cases. Third, households who live within 1 mile of transit are 12-21% likelier to use transit at least once daily across incomes and neighborhoods. Fourth, effects of transit access seem to be weakest on households with incomes between $25,000 to $50,000.

5.2.3. Regression Results for Research Question 2

Per Table 12, regressions run on VMT as the dependent variable confirm the earlier descriptive findings—household income is a negative and statistically significant predictor of VMT for incomes lower than $50,000 for each of the California metropolitan areas. In the Bay Area, living within a Half Mile Area is a negative and statistically significant predictor of household VMT; in San Diego, the continuous measure of distance to transit is a positive and statistically significant predictor of household VMT. Both of these findings suggest that the closer a household is to transit, the lower that household's VMT will be holding all else constant. Unlike the regressions for ***Research Question 1***, the interaction terms for ***Research Question 2*** with a dependent variable of VMT are rarely significant. In fact, the only interaction term that *is* statistically significant is for Los Angeles households with incomes less than $25,000 and living within Half Mile Areas. However, the total set of variables is jointly significant in every case, mirroring prior findings by Brownstone (2008).

Per Table 13, regressions run on GHG emissions as the dependent variable are more variable in terms of the predictive power of income. In Los Angeles and Sacramento, income is a significant and negative predictor of GHG emissions for incomes at or below $50,000; in the Bay Area, income is a significant and positive predictor for incomes between $50,000 and $100,000. Only in Los Angeles are any interaction effects significant. Namely, households within Half Mile Areas and who have incomes below $25,000 or between $50,000 to $100,000 have a significant reduction in GHG emission relative to other households.

5.2.4. Predicted Values from Regression Results for Research Question 2

Table 14 reports the predicted values for daily household VMT and GHG emissions across the various income categories. Similar to the descriptive statistics shown in Table 5, the predicted values for GHG emissions demonstrate that households within Half Mile Areas are expected to emit fewer GHG on a daily basis than those households outside Half Mile Areas, controlling for other factors. This trend in predicted values holds true across all four metropolitan areas, and is generally even clearer than what the descriptive statistics show. Nevertheless, the patterns in GHG emission reductions for Los Angeles and Sacramento households within versus outside Half Mile Areas are less clear than the patterns for Bay Area and San Diego households.

Table 12: Results for VMT Regressions, for 4 California metropolitan areas
Note: Sample excludes top 1% of VMT observations
Source: California Household Travel Survey 2010-2012

	Bay Area	Los Angeles	Sacramento	San Diego
Half-mile indicator	-13.99***	-2.844		
	(-4.40)	(-0.42)		
Distance			-0.183	0.715***
			(-1.46)	-3.21
Income <$25,000	-13.05***	-17.93***	-25.47***	-28.78***
	(-5.64)	(-10.65)	(-3.67)	(-4.97)
Income $25,000-$50,000	-6.851***	-10.17***	-16.61***	-15.39***
	(-3.94)	(-7.00)	(-3.02)	(-2.97)
Income $50,000-$100,000	-3.982***	-3.388***	-8.008*	-6.004
	(-3.06)	(-2.82)	(-1.86)	(-1.32)
Half-mile * Income <$25,000	-5.942	-17.91**		
	(-0.86)	(-2.16)		
Half-mile * Income $25,000-$50,000	-1.096	-13.48		
	(-0.18)	(-1.60)		
Half-mile * Income $50,000-$100,000	-3.795	-8.957		
	(-0.78)	(-1.09)		
Distance * Income <$25,000			0.283	-0.294
			-1.2	(-0.80)
Distance * Income $25,000-$50,000			0.204	-0.464
			-1.1	(-1.32)
Distance * Income $50,000-$100,000			0.157	-0.292
			-0.98	(-0.99)
Household Size	3.857***	3.133***	2.539**	4.810***
	-7.88	-8.21	-2.19	-4.69
# Vehicles in Household	15.90***	11.93***	11.16***	10.77***
	-23.49	-19.34	-6.34	-6.62
worker_count	6.340***	5.922***	6.291***	5.612***
	-8.27	-8.94	-3.39	-3.16
Constant	0.108	13.21***	23.35***	7.473
	-1.77	-8.17	-4.37	-1.46
Sigma	46.26***	51.76***	57.18***	46.40***
	-0.391	-0.345	-0.969	-0.944
N	7,844	12,239	1,881	1,337
Log-likelihood	-3.80E+04	-6.20E+04	-9.80E+03	-6.50E+03
F-statistic	191.73***	202.98***	20.41***	39.42***
Prob>F	0.000	0.000	0.000	0.000

*Dependent variable: VMT. Omitted category: income >$100,000. t-statistics in parentheses, other than for Sigma, where standard error is in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1. Distance used instead of half-mile indicator where too few households observed within 0.5 miles of rail transit (for Sacramento and San Diego).*

Table 13: Results for GHG Emission Regressions, for 4 California metropolitan areas
Note: Sample excludes top 1% of VMT observations
Source: California Household Travel Survey 2010-2012, EMFAC 2014 and fueleconomy.gov models

	Bay Area	**Los Angeles**	**Sacramento**	**San Diego**
Half-mile indicator	-2250.0^	4496.8*		
	(-1.79)	-2.06		
Distance			5.802	200.8*
			-0.14	-2.43
Income <$25,000	107.1	-2333.8***	-4717.0^	-2320.2
	-0.11	(-4.10)	(-1.94)	(-0.99)
Income $25,000-$50,000	-20.57	-1905.3***	-3287.2^	-1254
	(-0.03)	(-4.11)	(-1.85)	(-0.64)
Income $50,000-$100,000	1086.2*	-372.7	-712.1	-193
	-2.25	(-0.98)	(-0.51)	(-0.11)
Half-mile * Income <$25,000	1695.5	-6236.1*		
	-0.49	(-2.02)		
Half-mile * Income $25,000-$50,000	317.9	-4658.7		
	-0.13	(-1.64)		
Half-mile * Income $50,000-$100,000	-1810.5	-6715.1*		
	(-0.92)	(-2.50)		
Distance * Income <$25,000			50.86	-140
			-0.62	(-0.97)
Distance * Income $25,000-$50,000			50.88	-54.84
			-0.83	(-0.42)
Distance * Income $50,000-$100,000			39.35	114.8
			-0.76	-1.05
Household Size	72.73	188.8	-381.1	620.2
	-0.39	-1.51	(-0.99)	-1.53
# Vehicles in Household	11907.4***	10289.4***	12008.6***	10980.2***
	-31.8	-36.92	-14.04	-12.49
worker_count	1694.8***	1049.3***	1250.0*	1151.4^
	-5.86	-4.86	-2.02	-1.7
Constant	-2084.1**	1942.2***	2069.7	-1742.7
	(-2.98)	-3.65	-1.18	(-0.89)
Sigma	16243.9***	15632.0***	17404.4***	16244.8***
	-114.08	-142.29	-55.89	-46.99
N	6,548	10,183	1,576	1,113
Log-likelihood	1.00E-02	9.00E-03	8.00E-03	1.20E-02
F-statistic	161.62***	232.38***	31.58***	35.14***
Prob>F	0.000	0.000	0.000	0.000

*Dependent variable: daily CO_2 emissions (grams). Omitted category: income >$100,000. Excluding households with VMT greater than 99th percentile. t-statistics in parentheses, other than for Sigma, where standard error is in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1. Distance used instead of half-mile indicator where too few households observed within 0.5 miles of rail transit (for Sacramento and San Diego).*

As Figure 1 demonstrates, the patterns in predicted VMT reductions for households within Half Mile Areas versus outside differ from predicted GHG reductions in two ways. First, for a given metropolitan area, the predicted trend in VMT reduction by income stratum does not correlate well with the predicted trend in GHG reduction by income stratum. Second, how these trends differ also depends on the metropolitan area.

As an example of the first point – that predicted VMT reductions by income differ from predicted GHG reductions by income for a given metropolitan area – take the Bay Area's predicted differences for households earning less than $25,000 and households earning between $25,001 and $50,000. Households in the Bay Area earning less than $25,000 are predicted to substantially reduce their VMT; they are not predicted to substantially reduce their GHG emission. Conversely, households in the Bay Area earning $25,001-$50,000 are not predicted to substantially reduce their VMT, but *are* predicted to substantially reduce their GHG emissions.

As an example of the second point – that trends in VMT and GHG reductions by income differ across metropolitan areas – consider the four metropolitan areas shown in Figure 1. In particular, higher income households in the Bay Area (those earning $50,001-$100,000) are predicted to reduce their VMT the most out of all Bay Area households, whereas in San Diego the highest income households are predicted to reduce their VMT the most out of all San Diego households. In contrast, households earning less than $25,000 in the other two metropolitan areas are predicted to reduce their VMT the most.

Importantly, Figure 1 does not demonstrate that the disparities described above are statistically significant ones. Determining significance of Tobit predicted values is quite difficult. As an alternative, for each metropolitan area we tested the statistical significance of the linear combination of the interaction terms and either the Half Mile Area indicator (for the Bay Area and Los Angeles) or the continuous distance to transit measure (for Sacramento and San Diego). By constructing 95% confidence intervals for these linear combinations we are able to conclude whether the differences across metropolitan areas for a given income category are or are not significant. After conducting this exercise, we find that the predicted changes in VMT by income are not statistically significantly different between Los Angeles and the Bay Area; the same holds true for Sacramento and San Diego, other than for households earning above $100,000. Similarly, for predicted changes in GHG emissions by income, Los Angeles and the Bay Area's predicted trends in reduction are not dissimilar other than for households earning at least $100,000. For Sacramento and San Diego, only households earning $50,001-$100,000 have dissimilar predicted reductions in GHG emissions.

6. Discussion

This study's results show heterogeneous effects on VMT and on transit system usage (trips, mode share, probability) and income and certain heterogeneity by neighborhood type. Various explanations can be tested for why this may be the case.

First, the lower VMT decreases for lower-income households in transit-proximate Neighborhood Centers and Single Family Home Areas may suggest that these are not the locations that these households frequent for employment, recreation, or retail. Rather, they still need to drive to those locations. Perhaps these areas can not support, or tend to price out, the lower-wage services or manufacturing employment or lower-cost grocery and retail establishments frequented by lower-income households. In contrast, higher-income households may prefer the establishments located in lower-density neighborhoods.

Table 14: Predicted Differences for VMT and GHG Emissions between Households Residing within Half Mile Areas minus outside Half Mile Areas, for 4 California metropolitan areas
Note: Sample excludes top 1% of VMT observations
Source: California Household Travel Survey 2010-2012, EMFAC 2014 and fueleconomy.gov models

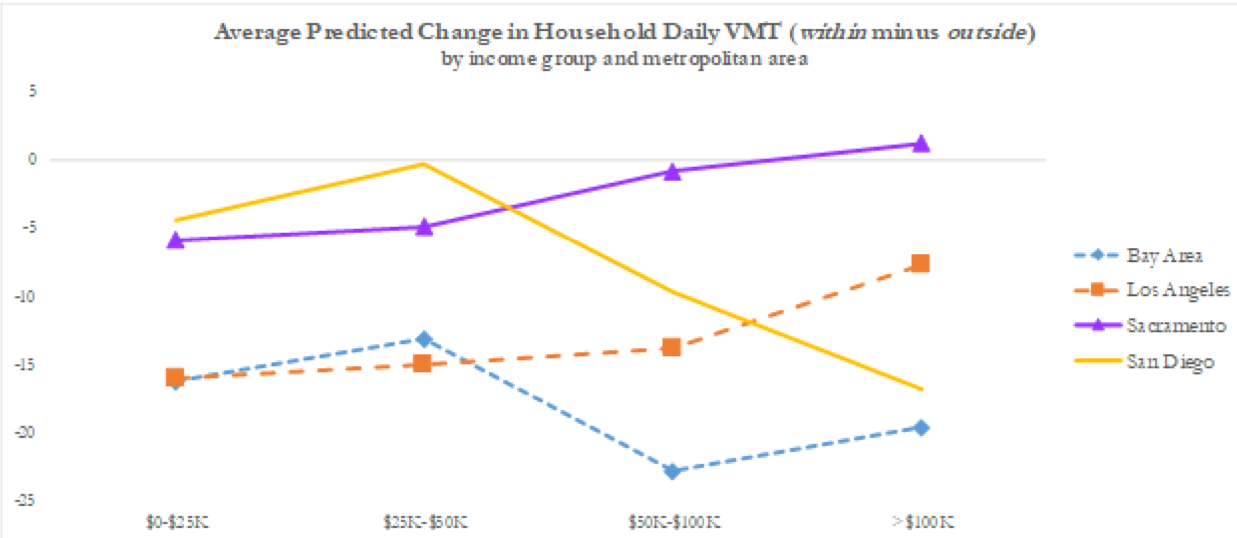
San Francisco Bay Area	**Average Predicted VMT**			**Average Predicted GHG Emissions**		
	Non-TOD	**TOD**	**Difference in VMT** ***(Within minus outside)***	**Non-TOD**	**TOD**	**Difference in Emissions** ***(Within minus outside)***
\$0-\$25,000	29.80	13.62	**-16.18**	15,470	15,338	**-133**
\$25,001-\$50,000	39.46	26.34	**-13.12**	16,567	15,648	**-919**
\$50,001-\$100,000	48.39	25.62	**-22.77**	19,753	13,614	**-6,140**
>\$100,000	58.68	39.10	**-19.58**	21,453	17,440	**-4,012**
All income levels	50.47	29.32	**-21.16**	19,911	15,799	**-4,112**

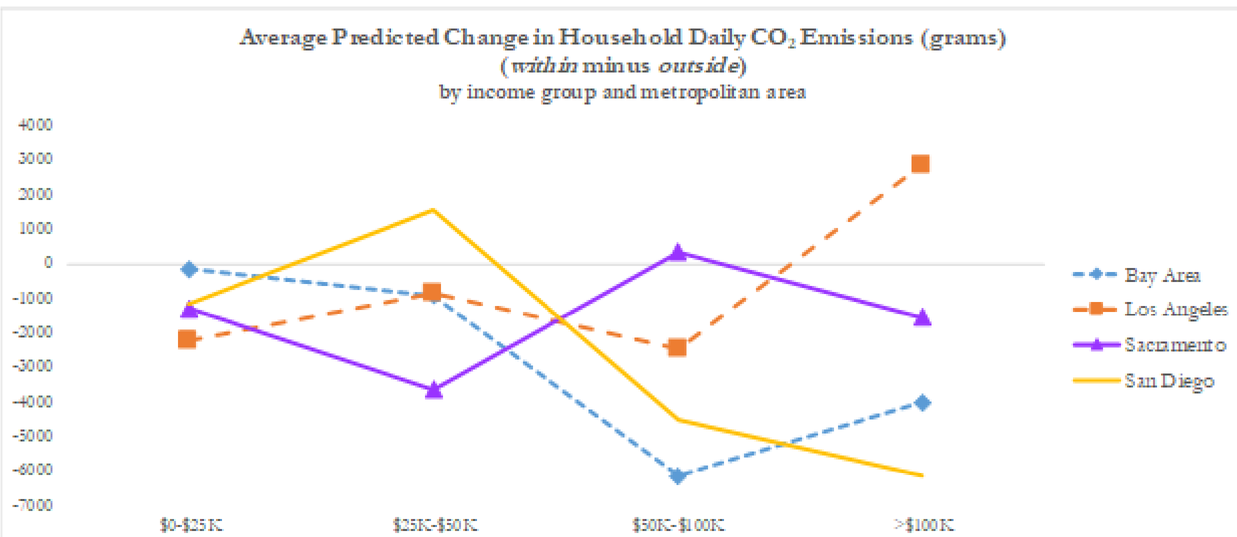
Los Angeles	**Average Predicted VMT**			**Average Predicted GHG Emissions**		
	Non-TOD	**TOD**	**Difference in VMT** ***(Within minus outside)***	**Non-TOD**	**TOD**	**Difference in Emissions** ***(Within minus outside)***
\$0-\$25,000	34.69	18.67	**-16.02**	15,416	13,185	**-2,231**
\$25,001-\$50,000	45.66	30.70	**-14.96**	16,707	15,876	**-831**
\$50,001-\$100,000	55.89	42.09	**-13.80**	19,837	17,369	**-2,468**
>\$100,000	64.03	56.37	**-7.66**	22,104	24,966	**2,862**
All income levels	53.29	33.47	**-19.83**	19,525	17,552	**-1,974**

Sacramento	**Average Predicted VMT**			**Average Predicted GHG Emissions**		
	Non-TOD	**TOD**	**Difference in VMT** ***(Within minus outside)***	**Non-TOD**	**TOD**	**Difference in Emissions** ***(Within minus outside)***
\$0-\$25,000	37.14	31.28	**-5.86**	14,912	13,630	**-1,282**
\$25,001-\$50,000	47.59	42.74	**-4.85**	17,503	13,877	**-3,626**
\$50,001-\$100,000	58.61	57.81	**-0.80**	21,271	21,626	**355**
>\$100,000	68.33	69.56	**1.23**	23,446	21,906	**-1,540**
All income levels	56.90	51.91	**-4.99**	20,651	18,247	**-2,404**

San Diego	**Average Predicted VMT**			**Average Predicted GHG Emissions**		
	Non-TOD	**TOD**	**Difference in VMT** ***(Within minus outside)***	**Non-TOD**	**TOD**	**Difference in Emissions** ***(Within minus outside)***
\$0-\$25,000	25.83	21.44	-4.39	14,643	13,490	-1,153
\$25,001-\$50,000	39.32	39.03	-0.30	17,092	18,674	1,582
\$50,001-\$100,000	54.60	44.88	-9.72	22,558	18,067	-4,491
>\$100,000	68.70	51.96	-16.73	24,953	18,838	-6,114
All income levels	52.88	36.76	-16.12	21,637	17,360	-4,277

Figure 1: Predicted Differences in Average Daily VMT and Average Daily CO2 Emissions Across Income Bands, for 4 California metropolitan areas
Note: Sample excludes top 1% of VMT observations
Source: California Household Travel Survey 2010-2012, EMFAC 2014 and fueleconomy.gov models





Second, measurement of transit trips, usage, and share reflect overall transit use – not just rail. Lower-income households are more likely to use transit in general, and buses in particular, compared to higher-income households (Santos et al., 2009). Thus, our findings may reflect a larger usage of bus transit by lower-income households in rail-proximate areas, which tend to be better served by all transit forms, given the need for multimodal transit connections. Hence, higher-income households' reductions in VMT may be due more to the rail service, while lower-income households' transit usage increase may be more due to the bus service.

Third, magnitudes of differences across travel behaviors are higher in Central Place neighborhoods for all income groups. Intuitively, more built up neighborhoods are more suited to TOD and transit-infused travel than single-family areas.

Our analysis of predicted patterns in household VMT reduction and household GHG reduction suggest a couple areas for future research as well. First, as depicted in Figure 1, the predicted reduction in household VMT (*i.e.*, within a Half Mile Area versus outside) for higher income households is smaller than lower income households for Sacramento and Los Angeles; this trend is opposite in San Diego and the Bay Area. These facts suggest that the rail systems of the latter two metropolitan areas provide greater access to local amenities and/or employment opportunities than the rail systems of the prior two metropolitan areas. While our data show that higher income households make more vehicle trips and fewer transit trips (Table 3), it is certainly possible there are endogenous differences across metropolitan areas. Therefore, it is possible that the variations noted above capture differences in the maturity and extent of metropolitan areas' rail transit systems.

Second, the predicted data (Table 6, Table 14, Figure 1) appear to confirm that differences in vehicle technology correlated with household income are an important factor to account for when using VMT as a proxy for GHG emissions. In particular, it appears that this correlation in technology with household income makes the translation of VMT to GHG emissions a nebulous one. Lower income households tend to drive fewer miles but tend to pollute more per mile. These facts suggest that future models incorporating both VMT and GHG should take a two-step approach, first predicting vehicle characteristics for a household and then predicting GHG emissions from the VMT associated with predicted vehicle characteristics. Furthermore, they suggest that the metropolitan areas' built environments likely play a key role in this relationship, justifying our neighborhood type analysis used to explore ***Research Question 1*** and suggesting a more granular analysis of GHG emissions at the same neighborhood type level.

7. Conclusion

This paper unpacks the potentially complex relationship between travel behavior, transit access and income, controlling for neighborhood characteristics. It further explores the translation of household VMT to household GHG emissions, and how this translation may differ across the four California metropolitan areas studied. We find that transit access leads to decreases in VMT for higher-income households regardless of the type of neighborhood in which they live, which is confirmed in our second analysis of household VMT at the metropolitan level. We also find that transit access leads to increases in system usage on a variety of measures, regardless of income and neighborhood, but that lower-income households' increase usage rates more than higher-income households. Finally, we find that while higher income households tend to reduce VMT the most when living near transit compared to far away, they may not tend to reduce GHG emissions the most due to a number of factors.

These results underscore the complexity of TOD planning today and over the past 25 years. To achieve environmental policy goals of reduced emissions through less driving, attracting higher-income households to live near transit gives the largest payoff in terms of VMT. Households with incomes over $100,000 reduce VMT by up to 7 miles per day than those making less than $50,000, especially in less dense neighborhoods. From an environmental perspective, siting rail transit through higher-income neighborhoods or building housing for a wealthier clientele may need to be part of the equation.

On the contrary, having a lower-income population using a city's rail system is better for transit system efficiency, especially in denser neighborhoods. While households of all incomes are almost 20% likelier to use transit when living within one mile of a station, it is the households with incomes below $25,000 which have the highest magnitude increases in trips (over 0.5 trips per day) and mode share increases (over 5% share increase). The social equity perspective also tends to support transit access for lower-income populations.

While this report deals with transit access generally, it is applicable to TOD planning specifically. Planners with existing or incoming rail systems need to think long and hard about the best recipe for an equilibrium among environmental, system efficiency, and social equity goals. It may be tempting to believe that the same policies benefit all of these perspectives at the same time, yet the data in this paper shows otherwise, even when neighborhood types are taken into account. Station-area plans and corridor plans need to perform scenario analyses and forecasts to understand how these varied travel behavior outcomes influence system- and region-level goals.

Though this paper lays out clear cross-sectional results, moving to a causal interpretation requires more work. Future research will need to compare travel survey results from different years in a longitudinal framework to better understand causal mechanisms. However, recent evidence suggests that cross-sectional estimates may be good enough approximations in many cases, since the effect of residential selection bias on travel behavior may be smaller than previously suspected (Brownstone, 2008; Duranton and Turner, 2016).

This paper suffers from several other limitations. First, due to small sample sizes, transit access was measured as a One Mile Area in our neighborhood type analyses, which may be a longer distance than usually considered (Guerra et al., 2012) and greater than the distance at which a household may choose to walk. Second, small sample sizes precluded direct interaction of neighborhood types and income and the usage of High Density Downtowns and Industrial / Employment Centers in the regression analysis. Third, a high number of surveyed households made no transit trips, potentially biasing the transit usage results, despite censoring corrections. Fourth, neighborhood types may differ by metropolitan areas. A more flexible neighborhood type definition may be needed to control for region-level heterogeneity. Fifth, our predictions of GHG emissions by household were directly inferred from household and vehicle characteristics. As aforementioned, future modeling work should employ a two-step approach that first predicts VMT and vehicle characteristics *from* household characteristics, and then predicts GHG emissions from these first-stage predictions.

As the predilection for TOD living grows, the next 25 years of TOD planning and research looks promising. Future research on the effects of TOD on travel behavior should more explicitly account for *which* station areas implement TOD plans and visions and which just have a transit station. Also, future work can integrate data on ride-sharing to better understand how they influence transit usage, VMT, and GHG emissions. Studies could also use multiple travel surveys to understand the dynamics of vehicle demand, before and after the arrival of transit and TODs.

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Supplementary Materials 1

The methodology to estimate station area statistics follows from Boarnet et al. (2017b).

We use 2009-2013 American Community Survey (U.S. Census Bureau, 2013a) and Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics Data (LODES) (U.S. Census Bureau, 2013b), reported for census tracts, for computing several neighborhood type statistics. We estimated population and employment in Half-Mile Areas surrounding each household's residential address (obtained from the CHTS 2010-2012) using spatial interpolation. Interpolation was necessary since Half-Mile Areas around households tended to be comprised of multiple census tracts, with some tracts crossing the border of the Half-Mile Area.

A. Estimated population and employment *C* for Half-Mile Area around household address *S* is derived as:

$$C_s = \sum_{n=1}^{N} \frac{C_n A_{ns}}{A_n}$$

Where:
S contains *N* census tracts in full or in part;
Census tract is denoted by *n (n=1, 2… N)*;
C_n = population or employment of census tract *n* (available directly from ACS / LODES data);
A_n = total area of census tract *n*;
A_{ns} = area of census tract *n* contained within station area *S*