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Transportation Impacts of Affordable Housing: Informing Development Review with Travel Behavior Analysis

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Transportation impacts of affordable housing: Informing development review with travel behavior analysis

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Abstract: Planning for affordable housing is challenged by development policies that assess transportation impacts based on methodologies that often do not distinguish between the travel patterns of residents of market-rate housing and those living in affordable units. Given the public goals of providing affordable housing in areas with good accessibility and transportation options, there is a need to reduce unnecessary costs imposed by the potential overestimation of automobile travel and its associated impacts. Thus, the primary objective of this paper is to examine and quantify the influences of urban characteristics, residential housing type, and income on metrics commonly used to assess the transportation impacts of new development, namely total home-based trips and home-based vehicle trips. Using the 2010-2012 California Household Travel Survey, we regressed these metrics on urban place type, regionally adjusted income, and housing type, controlling for household size, weekday travel, and home location. The results indicate significant reductions in vehicle trip making with lower incomes and increasing urbanization. These findings support more differentiation of affordable and market-rate housing in the development review process and emphasize the need for development standards to be more sensitive to the characteristics of future residents and location.

Keywords: Trip generation, affordable housing, transportation impact analysis, low-income, land use

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1 Introduction

The development-review process generally requires an evaluation of the anticipated additional transportation demand that new development places on the system and an assessment of fees or improvements to mitigate of these impacts. However, industry standard guidelines for assessment of travel demand are

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outlined within the Institute of Transportation Engineers (ITE) *Trip Generation Handbook* (Institute of Transportation Engineers, 2014) with data provided by the *Trip Generation Manual* (Institute of Transportation Engineers, 2012). These professional resources have been focused solely on vehicle trip rates for these traffic impact analyses.

This approach has long been criticized as having limitations regarding the insensitivity of these sources to urban contexts, socio-demographics of system users, and non-automobile transportation choices, despite the wealth of research accumulated on their importance in shaping travel behavior (Clifton, Currans, & Muhs, 2013; Weinberger, Dock, Cohen, Rogers, & Henson, 2015; Millard-Ball, 2015). As a result of this insensitivity, there may be undue costs placed on affordable housing projects, as methods may inaccurately estimate higher levels of vehicle use than are actually realized by residents. In addition, an overestimation of automobile demand may misdirect resources and create environments that are not supportive of the modes they do use.

There is a need to identify and analyze the extent to which these travel outcomes vary by these important characteristics. Using the 2010-2012 California Household Travel Survey, this paper explores how income, built environment measures, household size, and housing type relate to observed travel behavior, specifically in terms of trip generation (or trip frequency). The goal is to inform the current affordable housing policy debate by providing the anticipated differences in transportation outcomes between residents of affordable and market-rate units across different urban contexts. Specifically, we demonstrate how development policies may unduly penalize these projects if they do not account for the significantly lower rates of trip generation and use by their residents. Further, our analysis points to some key considerations for efficiently locating these units in areas that provide greater transportation choices.

The remainder of the paper is organized as follows. The next section of the paper provides a review of the policy context and the literature, followed by a description of the methodological approach. The results of two multivariate models examining travel outcomes are described in the fourth section, and finally a discussion of the trends in the conclusion.

2 Background

Households of limited means have fewer choices in both where they can afford to live and how they can travel. Nationally, the share of households residing in rental housing rose from 31% in 2005 to 37% in 2015, while household incomes receded back to 1995 levels (Joint Center for Housing Studies, 2015). The current supply of affordable rental housing has not matched this growing demand, as the rental vacancy rate has steadily declined while the rental market has tightened (Steffen et al., 2015). Most developers cannot build new affordable housing stock for low-income households without subsidies to close the growing gap between their construction costs and tenants' affordable rents (Joint Center for Housing Studies, 2015). Moreover, while low-income residents of these rental units may participate in programs to ease some of the burden of increasing housing costs, they are also likely to face higher transportation costs or more limited access to employment opportunities, medical needs, and other necessities (The Center for Neighborhood Technology, 2012).

For example, income is a key determinant of auto ownership (Pucher & Renne, 2003; Giuliano & Dargay, 2006; Blumenberg & Pierce, 2012). Given their limited access to personal automobiles, low-income adults are more likely to travel regularly by public transit (Giuliano, 2005). Beyond auto ownership, Ong and Houston (2002) found public transit use for commuting and job-searching purposes corresponds with an inability of low-income adults to access a vehicle and having poor or limited local bus service. Low-income households reported the cost of transit as a larger problem than households earning a higher annual income (Giuliano, 2005). As such, low-income groups also tend to walk more often for transportation (Pucher & Renne, 2003; Tal & Handy, 2010). Travel patterns resulting from the limited set of transportation options and household needs of priority populations include fewer person trips and less distance traveled (Murakami & Young, 1997; Pucher & Renne, 2003).

Constructing affordable housing developments in location-efficient neighborhoods, or those with environments that support non-automobile travel options, is a strategy for improving the access of low-income residents to both work and non-work activities. Travel to destinations becomes convenient as residential densities, public transit accessibility, mixed uses, and supports for pedestrian and cycling increase and as a result, vehicle ownership and use decline (Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002). In a recent California-based study aimed at addressing the issue of affordable housing as a climate strategy, Newmark and Haas (2015) found low-income households are likely to reside within location-efficient areas characterized by smaller dwellings, greater transit accessibility, and lower vehicle ownership rates. Chatman (2013) suggested that higher development density, greater local access to shops and services, and less parking could induce households of all income levels to drive less.

Unfortunately, the cost to construct affordable multifamily sites within location-efficient areas is becoming exceedingly expensive. Regulatory (e.g., zoning restrictions) and financing (e.g., insufficient government subsidies) obstacles limit the ability of rental housing developers to significantly add affordable multifamily housing stock. Accordingly, several cities are currently experimenting with reduced parking requirements to offer some regulatory relief to developers (Joint Center for Housing Studies, 2015). The construction of multifamily housing with less onsite parking allows developers to build more housing units for low-income households who are less likely to own vehicles and in urban contexts where non-automotive travel is feasible (Manville, 2013). Parking construction costs reduce the affordable housing supply and result in more expensive housing since these additional costs may be passed on to renters and/or households may have to pay for a parking space regardless of auto ownership status (Rowe, Morse, Ratchford, Haas, & Becker, 2014). Together, the impact of space devoted to parking and parking costs present two major barriers to providing persons of low-income with affordable housing options with strong regional and local access (Rogers, et al., 2016).

While the travel patterns and needs of low-income households have been documented in research, this information has yet to be incorporated into methods for reviewing the impacts of new housing development (Clifton et al., 2013; Schneider, Shafizadeh, Sperry, & Handy, 2013; Dock et al., 2015) and builds off of research focusing on housing and commercial land uses previously completed in California (Kimley-Horn and Associates, Inc., Economic & Planning Systems, & Gene Bregman & Associates, 2009; Schneider et al. 2015). The industry standards for estimating transportation impacts are the data and methods presented in the Institute of Transportation Engineers' (ITE) *Trip Generation Handbook* (2014); but as yet, there are no standard methods or available data to differentiate the transportation impacts of affordable housing developments (as compared to market-rate housing) across urban, suburban, or rural contexts in the U.S. This research aims to fill this gap by explicitly linking affordable housing development policies to the kinds of information, albeit limited, used in assessing transportation impacts during development review.

3 Data and methods

The 2010-2012 California Household Travel Survey (HTS) is used for this analysis. The survey sampled 42,431 households across all fifty-eight counties in California and participants agreed to complete a one-day travel diary, as well as provide socio-demographic and -economic information. Summaries for household-level trip making were computed from the trip segment data file by University of California, Irvine (Rindt, 2015) and provided by Caltrans as part of the HTS.

Based on our interests in linking our analysis to transportation-impact analyses, the travel outcome variables selected for the analysis are home-based vehicle trips and home-based person trips, all aggregated at the household level. These are commensurate with information used in state-of-the-practice trip generation analysis. Although travel behavior research has identified a large number of correlates with these travel outcomes, we limited the number and type of independent variables to mirror those factors that are available during development review stage of a project (pre-occupancy) and commonly used in transportation analyses. The independent variables include household size, dwelling type (single-family/multifamily housing), day of the week (weekday/weekend), household income (relative to affordable housing limits) and urban context at the place of residence. We controlled for weekday versus weekend travel using a single dummy variable because of expected differences in travel patterns between those two periods. Additionally, we controlled for potential differences in the large metropolitan areas of Los Angeles and San Francisco due to variations in the regional economies, urban spatial structures, and transportation options in those places.

4 Income qualifying limits for affordable housing programs

Income data are categorical in the HTS. Thus, the midpoint of each income category associated with a household was used to represent its income. California's Official State Income Limits for 2016 were used to relate each household's income to the qualifying limits for housing policy programs in each household's location and to control for regional economic variations (Bates, 2016). These annual qualifying income limits are used to determine eligibility for subsidized housing programs in California and are calculated by the Department of Housing and Community Development based on the US Department of Housing and Urban Development's (HUD) specification for below-market rates. *Median income* for each county is determined by HUD and based upon U.S. Census Bureau's American Community Survey (ACS) data, and a four-person household represents the basis for establishing limits.

Each household was then assigned to one of these income designations: extremely low-income, very low-income, low-income, median-income, moderate-income, or above moderate-income. These designations are determined relative to the median family income for a geographic area, known as area median income (AMI) in California. *Extremely low-income* households are households whose incomes do not exceed 30% of the area median income; *very low-income* households are households whose incomes are greater than 30% of AMI and do not exceed 50% of the AMI; and low-income households are those whose incomes are greater than 51% do not exceed 80%. *Moderate-income* levels are greater than 80% and no more than 120% of the county's AMI.

5 Place types

In this study, we developed a set of place typologies to capture the area-wide differences in the built environment based upon a set of indicators known to be associated with travel behavior outcomes, e.g., the "D's" (Ewing & Cevero, 2010) and accessibility (Handy, 1993). In order to better guide urban planning policy, Caltrans developed a suite of qualitative descriptions of place types in their 2010 Smart Mobility report to illuminate the difference in urban contexts (Caltrans, 2010). We utilized the Smart Mobility place type descriptions to inform the development of statewide, quantitatively driven place types used in our analysis. We used built environment data made available by the Environmental Protection Agency's Smart Location Database (EPA's SLDB) at the Census block group geography (U.S. EPA, 2014).

To classify each location into clustered place types, a discriminant analysis was used in order to place each zone into a unique category. To simplify the method of post-hoc location classification, we categorized the built environment in each of the 23,190 Census block groups in California based on a set of six characteristics: the population, employment, and intersection density in addition to percent of single-family housing units and proportion of jobs within a half mile of a fixed-service transit stop or 45 minutes via auto travel. Table 1 provides the descriptive statistics for each these measures per place type.

Each block group was then classified as one of five place types based on the variation in these built environment indicators. The procedure for place type assignment began by selecting all block groups with 80% of its area in an urban area (as defined by the US Census); those block groups deemed outside of urban areas were classified as non-urban. Each of six built environment variables were then manually divided into four intervals—first using standard breaks methods (e.g., Jenks breaks, clustering analysis), followed by manual modification of segments based upon examination of its distribution spatially. This inspection was iterative and involved an examination of variation across neighborhoods using online resources (e.g., Google StreetView); regional definitions of place types, e.g., (Caltrans, 2010); and local expertise (e.g., discussions within the research team, project panel, and sponsoring agency). Each block group was then assigned a score between one and four for each of the built environment measures depending on the interval where the calculated value of the measure was situated (e.g., a block group with no jobs would be given a value of one because it was situated in the category reflecting the lowest level of employment density). Then, the average of the scores across all six built environment characteristics was calculated for each block group and was used to assign the block groups into one of the four urban place types based on this mean interval score. Table 1 provides an overview of the break values used in creating these place types while Figure 1 displays their spatial representation throughout California.

These place types were then compared with the California results of a cluster analysis at the tract level conducted by Salon (2015). Generally, the place types were similar to those constructed by Salon, indicating relatively similar results between the two methods: clustering analysis and mutually exclusive breaks.

Each household in the study was assigned a place type based upon the classification of the Census block group of their residential location. Place types are useful for understanding the immediate context in which travel takes place. However, these places do not exist in a vacuum and the larger metropolitan structure in which they reside is an important consideration when evaluating travel. For example, an area categorized as an "urban district" in San Francisco will have similar features as an area in the same category located in Los Angeles; but the larger urban structure of each metropolitan area will also exert influence on travel choices. To this end, we introduce controls at the county level to test for the additional effects of the built environment at a larger scale.

6 Travel outcomes

To evaluate the relationship between household-level travel outcomes (home-based vehicle trips and total home-based person trips), we regressed each of these outcomes on income, place types, dwelling type, household size, weekday/weekend travel day, and county (see Table 2 for descriptions of all these variables). Because the transportation impacts of new development are assessed by the number of dwelling units, each outcome was predicted at a household-level aggregation.

All models were estimated with a negative binomial regression to accommodate the count-based nature of these data. We controlled for the impacts of individual counties on these trips but only Los Angeles and San Francisco counties were significant. For each model, interactions between place types, income categories, dwelling types, and counties were tested, but only those interactions in the home-based vehicle trip model provided statistical significance for interpretation, and therefore, only these interactions were included. The square of household size was included to examine the diminishing effect contributed by each additional person in the household. The statistically significant income category of Refused or Unknown was included in the models to control for any bias in this group. While developing the models, the Alkaline Information Criterion (AIC) was used to determine if variables contributed to explaining deviance existing in the models—models with decreasing AIC were deemed "improved."

Table 1: Descriptive statistics and interval score breaks for built environment indicators per place type

Place Type:	**Urban Core**		**Urban District**		**Urban Neighborhood**		**Suburban Neighborhood**		**Non- Urban**	
Indicator	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Population per Acre	67	48	42	25	27	14	11	8	<0	<0
Employment per Acre	58	96	17	41	7	13	2	4	<0	<0
Percent of Single-Family Housing	0.06	0.07	0.19	0.20	0.39	0.25	0.76	0.25	0.81	0.18
Intersections per Square Mile	213	148	165	111	126	79	85	47	5	8
Percent of Jobs in 0.5-mile of Transit Stop	0.93	0.21	0.45	0.45	0.19	0.34	0.03	0.13	0.00	0.01
Number of Jobs in 45 Mins. of Auto Travel	509,569	186,240	513,498	176,351	466,294	163,922	211,857	179,250	26,942	45,325
Interval Score Breaks										
Population per Acre	80		40		20		< 20		N/A	
Employment per Acre	100		25		10		< 10		N/A	
Percent of Single-Family Housing	0.15		0.50		0.75		> 0.75		N/A	
Intersections per Square Mile	250		175		100		< 100		N/A	
Percent of Jobs in 0.5-mile of Transit Stop	0.95		0.50		0.10		< 0.10		N/A	
Number of Jobs in 45 Mins. of Auto Travel	400,000		300,000		200,000		< 200,000		N/A	
Mean Interval Score Break	3		2.5		2		1		N/A	
Number of Block Groups	317		714		3,074		17,151		1,934	

Notes: Sample size (n) is 23,190 US Census block groups.

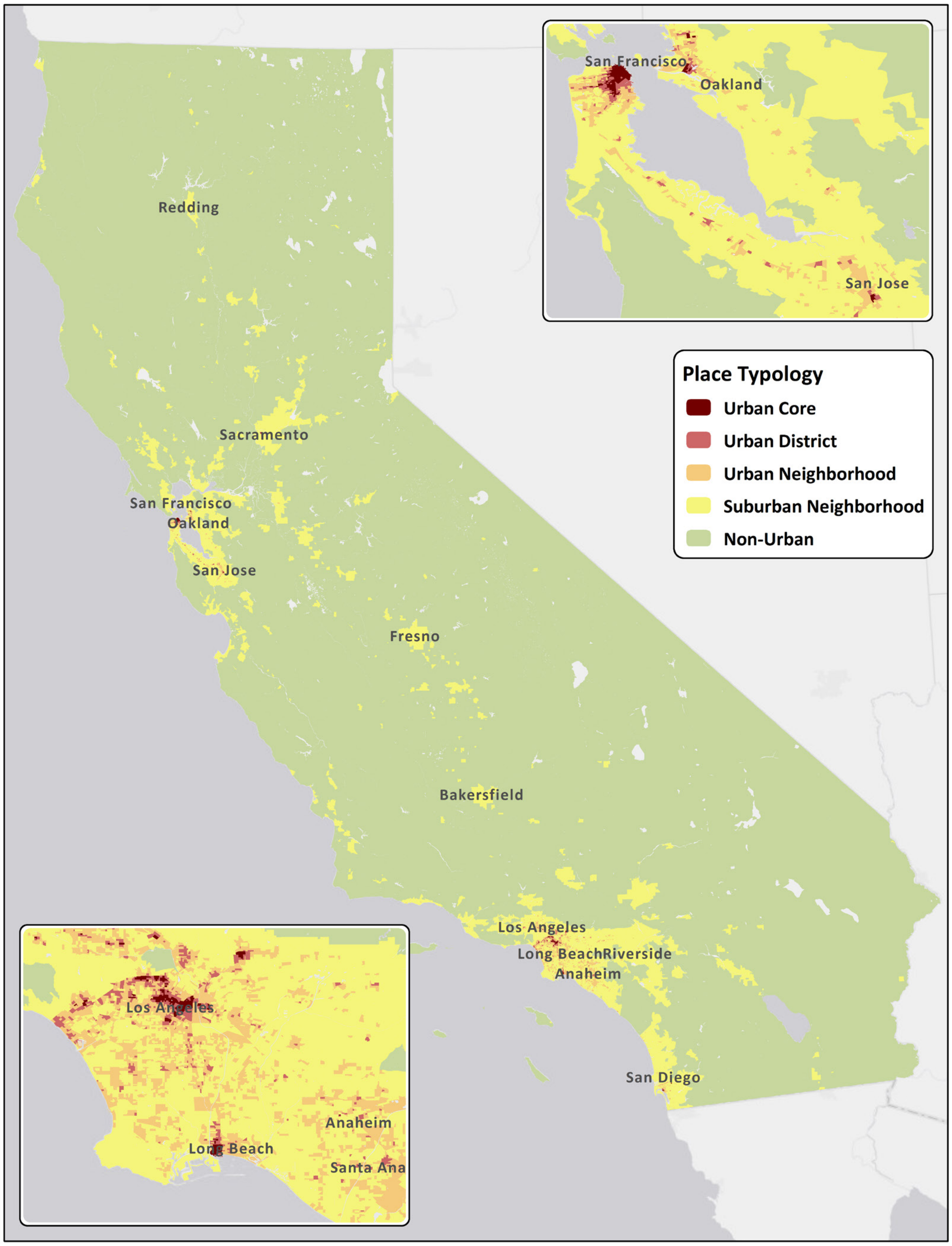

Figure 1: Place typologies applied to California

Table 2: Description of the travel data used in model estimation

Dependent Variables	Descriptions	Mean	Standard Deviation
Home-Based Person Trips	Count of daily home-based trips by household (any mode)	5.21	4.73
Home-Based Vehicle Trips	Count of daily home-based vehicle trips by households	2.99	2.66
Independent Variables	**Descriptions**	**Proportion[1]**	
County			
Los Angeles	Respondent lives in Los Angeles County	20%	
San Francisco	Respondent lives in San Francisco County	3%	
Multifamily Housing Unit	Respondent lives in a multifamily housing unit	15%	
Household Size	Size of respondent's household	2.57	
Household Size Squared	Size of respondent's household, squared	8.50	
Weekend Travel (Fri-Sun)	Travel day was Friday, Saturday, or Sunday	43%	
Household Income			
Above Moderate-Income	> 120% of the area median income	40%	
Moderate-Income	81-120% of the area median income	14%	
Low-Income	51-80% of the area median income	15%	
Very Low-Income	31-50% of the area median income	10%	
Extremely Low-Income	≤ 30% of the area median income	12%	
Refused or Unknown		9%	
Place Type	See descriptions in the text		
Urban Core		2%	
Urban District		2%	
Urban Neighborhood		9%	
Suburban Neighborhood		73%	
Non-Urban		15%	
Automobile Mode Share by Place Type		**Proportion**	**Trips (n)**
Urban Core		41%	3,551
Urban District		62%	6,378
Urban Neighborhood		74%	25,299
Suburban Neighborhood		88%	227,271
Non-Urban		92%	39,074

Notes: [1]Total households: 42,426

Table 3: Negative binomial regression model estimates for total home-based person trips (any mode) and total home-based vehicle trips

Travel Outcome:	Home-Based Vehicle Trips				Home-Based Person Trips (Any Mode			
	Model 1				Model 2			
Variable	B	SE	p	Exp(B)	B	SE	p	Exp(B)
Intercept	**-0.35**	0.07	0.00	0.71	**0.37**	0.04	0.00	1.44
County								
San Francisco	**-0.25**	0.04	0.00	0.77	0.04	0.03	0.19	1.04
Los Angeles	**0.43**	0.10	0.00	1.53	-0.01	0.01	0.21	0.99
Multifamily Housing Unit	**-0.17**	0.01	0.00	0.84	0.00	0.01	0.94	1.00
Household Size	**0.53**	0.01	0.00	1.70	**0.70**	0.01	0.00	2.02
Household Size Squared	**-0.05**	0.00	0.00	0.96	**-0.05**	0.00	0.00	0.95
Weekend Travel (Fri-Sun)	**-0.18**	0.01	0.00	0.83	**-0.09**	0.01	0.00	0.91
Household Income								
Above Moderate-Income	(base)				(base)			
Moderate-Income	**-0.09**	0.01	0.00	0.92	**-0.07**	0.01	0.00	0.93
Low-Income	**-0.16**	0.01	0.00	0.85	**-0.12**	0.01	0.00	0.89
Very Low-Income	**-0.34**	0.02	0.00	0.71	**-0.21**	0.01	0.00	0.81
Extremely Low-Income	**-0.60**	0.02	0.00	0.55	**-0.23**	0.01	0.00	0.79
Refused or Unknown	**-0.19**	0.02	0.00	0.82	**-0.14**	0.01	0.00	0.87
Place Type								
Urban Core	(base)				(base)			
Urban District	**0.47**	0.08	0.00	1.60	-0.01	0.04	0.73	0.99
Urban Neighborhood	**0.64**	0.07	0.00	1.90	-0.03	0.04	0.36	0.97
Suburban Neighborhood	**0.69**	0.07	0.00	2.00	**-0.08**	0.04	0.03	0.92
Non-Urban	**0.52**	0.07	0.00	1.69	**-0.28**	0.04	0.00	0.75
Interaction Variable								
Los Angeles County *								
Urban District	**-0.33**	0.11	0.00	0.72				
Urban Neighborhood	**-0.42**	0.10	0.00	0.66				
Suburban Neighborhood	**-0.41**	0.10	0.00	0.66				
Non-Urban	**-0.49**	0.12	0.00	0.61				
Model Summary								
Observations (n)				41,021				41,021
Deviance				50,351.47				49,600.21
Alkaline Information Criterion				173,521.38				206,792.82
Log Likelihood				-86,739.69				-103,379.41

7 Results

The model results are presented in Table 3. Models 1 and 2 are negative binomial models regressing home-based vehicle trips and home-based person trips respectively upon the independent variables. To interpret the effect size of the model coefficients, we examine the exponent of the coefficients, which, for both model types allows us to examine the relationship of each variable with the respective travel outcome. For example, when values of exp(B) are higher than one, this indicates a positive relationship between the travel outcome measures and the corresponding independent variable and vice versa.

The results show high levels of significance for nearly all of the independent variables with a few notable exceptions. The square of household size as well as the main effect are significant, in both the estimated coefficients as well as the contribution to explaining variance and deviance in the models.

While the main effects of household size indicate a positive relationship in the models, the square of household size is negative, indicating a diminishing relationship between each additional member of the household and each outcome—potentially representing the transportation efficiencies existing in multi-member households.

As households locate farther from the urban core (treated here as a base case), they make increasing vehicle trips. As their income decreases relative to the county median, households tend to make fewer trips and are less likely to drive. Compared to their single-family housing counterparts, households that live in multifamily units make approximately 16% fewer home-based vehicle trips.

We observe a significant mediating relationship of a Los Angeles County indicator on place type for home-based vehicle trips (Model 1), suggesting a significant relationship between place types and each outcome for Los Angeles (LA) County, compared with all other counties. These results indicate households in the urban core and urban district in Los Angeles make approximately 54% and 10% more home-based vehicle trips than those in the same place types in other areas of the state (except San Francisco). For urban and suburban neighborhood place types, households in LA make approximately 1-2% more home-based vehicle trips compared with other areas of the state. In non-urban areas, LA households generate approximately 6% fewer trips compared to non-urban areas in the rest of the state. Households in San Francisco generally make 23% fewer home-based vehicle trips for all place types compared to households in all other counties. Although we tested the contribution of mediating effects of San Francisco County with place types, there was not enough evidence to suggest a significant relationship.

To better illustrate the magnitude of these effects of the independent variables, the predicted travel outcome of home-based vehicle trips is shown in Table 4. The effects are shown relative to a four-person household with an income above the moderate level, living in a single-family housing unit in a suburban place (the base case). These results are also plotted against the trip data provided in the ITE *Trip Generation Manual* (Institute of Transportation Engineers, 2012) for Land Use Code (LUC) 220 Residential Apartment in Figure 2. This graphic illustration shows the degree of overestimation of vehicle trips when urban context and resident incomes are not included.

There have been recent advances in the way that we assess the transportation impacts of new development. Many cities are moving away from reliance solely on vehicle trip data provided by ITE's *Trip Generation Manual* and collecting new multimodal data for a variety of land uses. In the latest edition of the *Trip Generation Manual* (9th edition), recommended practice is to start with assessment of the person trips generated by a development and then estimate how those trips are distributed across various modes. For this reason, we estimate models of home-based person trips in Table 3, Model 2.

The most notable result for the person trip estimation is that they appear to be less sensitive to place type than vehicle trips. Here, the parameter estimates for urban district and urban neighborhood are not significantly different from urban core (the base case). Suburban and rural places have significantly different and decreasing impacts on person trips. This is somewhat consistent with the notion put forth by ITE and others that residential person trips should be less variable by urban place type (Currans, 2017; Institute of Transportation Engineers, 2014), unlike the distribution of trips across various modes (including vehicle trips). This consistency across urban areas may be due to people substituting vehicle trips for walk, bike, and transit trips in more urban areas. Home-based person trip frequencies are also sensitive to income, with trip rates decreasing as income decreases. This suggests that although person trip rates may be a better starting point for evaluating site-level trip generation, the methods for evaluating transportation impacts should still consider socioeconomics of trip makers in the analysis.

Table 4: Predicted home-based vehicle trips (Model 1) relative to base case scenario

Income Category	Non-Urban	Suburban Neighborhood	Urban Neighborhood	Urban District	Urban Core
Single-Family Dwellings					
Extremely Low-Income	46%	55%	52%	44%	27%
Very Low-Income	60%	71%	67%	56%	35%
Low-Income	72%	85%	81%	68%	42%
Median/Moderate-Income	77%	92%	87%	73%	46%
Above Moderate-Income	84%	**100%**	95%	80%	50%
Multifamily Dwellings					
Extremely Low-Income	39%	46%	44%	37%	23%
Very Low-Income	50%	60%	57%	47%	30%
Low-Income	60%	71%	68%	57%	36%
Median/Moderate-Income	65%	77%	73%	61%	38%
Above Moderate-Income	71%	84%	80%	67%	42%

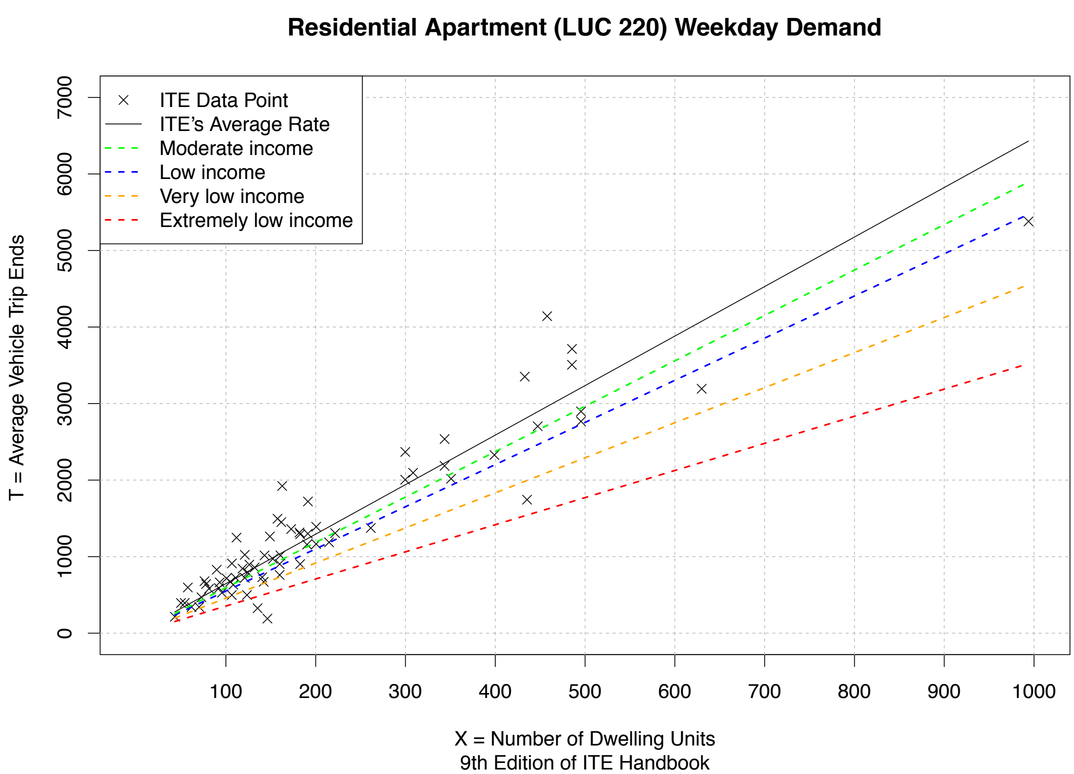

Figure 2: ITE residential apartment (LUC 220) weekday vehicle trips compared to home-based vehicle trip estimates from Model 1

8 Implications for affordable housing development

Many impact fee rates are developed using methodologies based upon vehicle trip estimates from ITE. If these rates are not sensitive to the issues we have been discussing—urban context and socioeconomics—they assume that all housing development will have same impact. Some fee structures fail to distinguish between multifamily and single-family development and assess the same fees on all residential development. To further demonstrate the implications of these shortcomings on development costs, we extend this analysis to consider the impact fees in two case study areas—Sacramento and Pasadena, California. We obtained the most recent impact fees for these locations (City of Sacramento, 2017; City of Pasadena, 2015) and adjusted them relative to the differences in travel outcomes by income and place type using the comparisons from Table 4. Table 5 shows the amount that each unit would be over-assessed based upon the relative differences in travel impact for the location and income of residents.

We did not control for any programs, discounts, or overlay zones that these jurisdictions may have in place to reduce fees for affordable housing or developments that are efficiently located with respect to transportation options. This exercise is strictly meant as an example to illustrate the potential additional costs that may be incurred by developers when impact analysis fails to control for differences in travel by income and location.

When one considers that most affordable housing development is multifamily and thus has many units per development, these errors can accumulate and have a marked impact on cost. For example, a developer of a 50-unit affordable apartment building targeted for residents in the low-income category in an Urban District neighborhood in Pasadena would be overcharged $59,238 in transportation impact fees. That same development in Sacramento would be overcharged $13,353. This number is lower because Sacramento has different rates for single-family and multifamily housing; thus, accounting explicitly for some of the travel differences between residents of different dwelling types which is corroborated by our analysis. These are not insignificant amounts in a project pro forma particularly given that fees are assessed for other utilities and services beyond transportation.

9 Discussion and conclusion

With an interest in contributing to affordable housing development policies, this analysis examined and quantified the relative influences of urban place type, residential dwelling type, and income on the travel outcomes that are most relevant in evaluating the transportation impacts of new developments. These results show significant differences in these travel outcomes between income groups and a strong association with place type, as well as contribute to understanding the interaction effects between the two. This strongly suggests that applying traditional methods and data to evaluate the transportation impacts of affordable housing developments will overestimate vehicle use and likely result in excessive fees and unwarranted mitigations.

The significant mediating relationship of LA County on place type also indicates that there is something about the relationship between residents and the built environment that results in significantly different home-based vehicle trips, even with a similar built environment. This may indicate that metropolitan structure or regional accessibility should be considered in addition to the local contextual variables. Another possible interpretation may have to do with the variation existing in categorical definitions of place—a common simplification of continuous, highly correlated variables to derive something more easily applied and assessed in practice. Either way, these results suggest that aggregating nationally collected data without providing more detailed contextual information—e.g., city or county, continuous built environment measures—may result in severe over- or under-estimation of behavior due to regional differences in how residents interact with similar built environments.

This analysis is not without limitations. First, our analysis was not conducted with explicit data from residents of affordable housing. Rather, we used income designations to identify households that would qualify to live in affordable housing in their area and discriminated by dwelling type. As a result, our conclusions may overstate the trip making differences because residents of affordable housing may have lower housing costs than similarly situated households living in market-rate housing and thus may have more resources to devote to activities and travel.

Second, our models are not intended to be sensitive to the full complement of household resources, environmental conditions and policies known to impact travel behavior. Despite having access to much of this information for the households in our data, we specifically limited our choices of independent variables to those that would be available to an analyst at the time a new development is proposed and under review. In those cases, the development is not yet built and thus the specific characteristics of the household are unknown, other than the targeted income qualifying limits for the housing. Third, we do not consider the role of self-selection bias in these results. However, low-income households have more constrained choices in where to live and perhaps self-section bias considerations can be relaxed. Fourth, while we considered on-site parking requirements in our discussion we were not able to include parking information as a variable in our model. Any data collected for an alternative rate study will be submitted to the City as a part of the official record and may be used in future rate calculations. The relationship between on-site parking requirements, vehicle ownership and trip generation warrants additional study. Finally, the development of place types was based upon the context of California and thus, may not fully represent the environments in other locations. Regardless, the findings here offer important direction for housing and transportation policy in the United States more broadly.

The contribution of the models estimated in this paper is that they are a) sensitive to regionally adjusted household incomes and the characteristics of the proposed sites, and b) based upon the observed travel behavior of residents, rather than merely vehicle counts. Therefore, using these results to estimate the travel outcomes for new housing developments may provide more robust estimates than the existing tools available today. These results also punctuate the need to understand how commonly used trip generation data vary from one region to the next. Without detailed information about how ITE's rates developed from sources across the nation were derived (e.g., urban and social context), application of these methods in urban areas may place additional burden on low-income housing developers and the corresponding residents.

Table 5: Amount of overassessment of impact fees relative to travel impacts

City of Sacramento				
Income Category	**Suburban Neighborhood Over-assessment per unit**	**Urban Neighborhood Over-assessment per unit**	**Urban District Over-assessment per unit**	**Urban Core Over-assessment per unit**
Single-Family Dwellings - Transportation impact fee of $1,182.00 per unit				
Extremely Low-Income	$533	$566	$665	$858
Very Low-Income	$344	$387	$515	$764
Low-Income	$178	$230	$382	$681
Median/Moderate-Income	$99	$154	$319	$641
Above Moderate-Income	$0	$60	$240	$592
Multifamily Dwellings - Transportation impact fee of $827.00 per unit				
Extremely Low-Income	$446	$465	$523	$636
Very Low-Income	$334	$360	$434	$581
Low-Income	$237	$267	$357	$532
Median/Moderate-Income	$190	$222	$319	$509
Above Moderate-Income	$132	$167	$273	$480
City of Pasadena				
Income Category	**Suburban Neighborhood Over-assessment per unit**	**Urban Neighborhood Over-assessment per unit**	**Urban District Over-assessment per unit**	**Urban Core Over-assessment per unit**
Single-Family Dwellings - Impact fee of $2,747.20 per residential unit				
Extremely Low-Income	$1,240	$1,317	$1,546	$1,994
Very Low-Income	$801	$900	$1,196	$1,775
Low-Income	$415	$534	$888	$1,582
Median/Moderate-Income	$229	$358	$741	$1,489
Above Moderate-Income	$0	$140	$558	$1,375
Multifamily Dwellings - Impact fee of $2,747.20 per residential unit				
Extremely Low-Income	$1,480	$1,545	$1,737	$2,114
Very Low-Income	$1,111	$1,195	$1,443	$1,930
Low-Income	$787	$887	$1,185	$1,768
Median/Moderate-Income	$631	$739	$1,061	$1,690
Above Moderate-Income	$438	$556	$907	$1,594

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