# Improving Transportation Impact Analyses for Subsidized Affordable Housing Developments in California:

***A Data Collection and Analysis of Motorized Vehicle and Person Trip Generation***

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## ABSTRACT

Transportation impact analyses begin with a trip generation estimation process—estimating motorized vehicle and person trip counts coming and going from the proposed site. Data commonly used is often insensitive to urban contexts (such as employment densities) and socioeconomic conditions. This insensitivity results in sometimes exaggerated estimates, an increase associated transportation impact fees, and a need for additional mitigation of impacts which may further hinder land development. In this study, we collected and analyzed person and motorized vehicle count data from 26 affordable housing developments in Los Angeles and San Francisco. Counts were regressed upon site and built environment characteristics known to influence site-level travel behavior (e.g., parking supply, employment density), and regressions were validated using externally collected data. The findings indicate the average square footage of dwelling units, parking ratios, and nearby retail employment densities to be important predictors. The findings also indicate that increasing the parking supply from one space to two for each dwelling unit will result in a significant predicted increase of approximately 0.26 and 0.18 motorized vehicle trips per dwelling unit for AM and PM peak periods, respectively. These findings reiterate the need for trip generation methodologies sensitive to the built environment and sociodemographics.



*Keywords*: trip generation, transportation impact analysis, motorized vehicle trips, person trips, affordable subsidized housing, parking supply

**HIGHLIGHTS**

- This manuscript describes the data collection and analysis of transportation impacts at 26 subsidized affordable housing developments in the San Francisco and Los Angeles study areas in 2017.
- Four models were developed estimating motorized vehicle and person trip counts for the AM (7:00AM-10:00AM) and PM peak hour (4:00PM-7:00PM) periods, as defined by industry standards.
- A validation sample from an external data collection was used to test the predictive power of the AM peak hour and PM peak hour motorized vehicle trip count that models estimated.
- The number of dwelling units and parking ratios (spaces supplied per dwelling unit) on site were significant and positive predictors of motorized vehicle trip generation counts for both peak periods.
- The following predictors were found to be consistent, significant, and positive predictors of person trip counts: dwelling units, average square footage of dwellings, and nearby retail employment density.
- The regression results predict that increasing parking supply from 1.0 to 2.0 parking spaces per dwelling unit would result in an increase of 0.26 motorized vehicle trips per dwelling unit in the AM peak and 0.18 motorized vehicle trips per dwelling unit in the PM peak—all other variables taken at the average observed value.

# INTRODUCTION

As the industry standard, the methods presented in the Institute of Transportation Engineers' (ITE) *Trip Generation Handbook* (Institute of Transportation Engineers 2014) and corresponding data within the *Trip Generation Manual* (Institute of Transportation Engineers 2012) represent current practice for evaluating the transportation impacts of new development. Trip generation counts are cordon counts that capture the universe of people or motorized vehicles coming and going to any site, generally defined as 'trip ends' or 'trip counts.' Historically, these methods focused on the collection and estimation of suburban motorized vehicle trip counts. However, the methods presented in these updated texts have since aimed to correct the long-standing criticism of problematic urban applications (Clifton, Currans, and Muhs 2013; Millard-Ball 2015; Weinberger et al. 2015; Shoup 2003) by adding information, updating methods, and discussing existing research to account for low- to high-density urban, multimodal area types (Clifton, Currans, and Muhs 2013; Weinberger et al. 2015; Schneider et al. 2013; Ewing et al. 2019).

There are no standard methods for estimating transportation impacts specific to affordable housing developments in the U.S. Despite extensive research on the travel outcomes and patterns of low-income households, this research has not been integrated effectively into data collection and estimation methods (Clifton, Currans, and Muhs 2013; Schneider et al. 2013; Dock et al. 2015). This gap in the research fails to connect how demographic characteristics, such as motorized vehicle ownership (Murakami and Young 1997; Pucher and Renne 2003; Blumenberg and Pierce 2012), might differentiate trip rates observed between affordable housing developments and their market rate counterparts. Concurrently, research relating trip generation to built environment characteristics (population and employment density, regional setting) and certain site characteristics (parking supply, average bedroom size) is limited, further hindering the development of more robust estimation methods.

We address this gap by collecting and analyzing data at 26 affordable housing developments located across multiple urban place types in California. Augmenting these data with other trip generation and built environment information, we developed models to predict person-trip and motorized vehicle-trip generation rates for affordable multifamily housing that can be used in future transportation impact studies. It is important to note that the purpose of this study was not to compare subsidized versus market rate dwellings; instead, we aimed to collect and analyze as many subsidized affordable developments in as many different urban form contexts as possible. In our analysis, we provide a comparison between our data and data conventionally used for Transportation Impact Studies or TIS (representing market rate, suburban, apartments). However, comparing our data with other urban market rate developments proved problematic, and we discuss this issue further in the conclusions.

# BACKGROUND

Over the past decade, several new studies have emerged improving the practice of evaluating transportation impacts at new development. However, even as new data is being collected, many new approaches continue to rely on ITE's data as a "base estimate" from which new data or models adjust. Weinberger et al. (2015) compared five methods for estimating urban trip generation at 16 sites, including market-rate multifamily developments, restaurants, and grocery stores. Aside from ITE's conventional approach (2014), the four innovative approaches tested all used ITE's estimates to apply urban-oriented adjustment models (Currans and Clifton 2015; Schneider, Shafizadeh, and Handy 2015; Ewing et al. 2011; Nelson/Nygaard 2005). Even as new data are collected, few studies have collected enough data within any one land use category to directly estimate demand for developments across urban areas.

In Weinberger et al. (2015), all five existing methods statistically controlled for the expected variation in travel patterns based on any changes in urban form from a suburban base case (Institute of Transportation Engineers 2014) to urban context described by individual or composite built environment measures. Results indicated a range of success for all methods in reducing the amount of error from ITE's suburban-based estimates; however, some methods over-predicted (Schneider et al. 2013; Ewing et al. 2011; Nelson/Nygaard 2005), while other methods under-predicted motorized vehicle trips (Schneider et al. 2013; Currans and Clifton 2015; Schneider, Shafizadeh, and Handy 2015), depending on the period of analysis. The authors concluded that the small sample size of data representing the spectrum of urban contexts would continue to limit understanding of expected urban transportation impacts (Weinberger et al. 2015), suggesting a continued need for more data collection, particularly throughout cities.

In one of the few studies to assess the trip generation impacts of affordable housing, Yam, Whitfield, and Chung (2000) analyzed "low- to middle-income" public housing estates in 274 developments in Hong Kong, which included more than 845,000 apartments and nearly three million residents. Although the culture and setting of Hong Kong varies greatly from the U.S. context, some findings transcended these differences. Number of dwelling units (consistent with ITE's standard approach), number of parking spaces, and average household size were significant in estimating urban multifamily trip generation rates. However, the authors did not control for the relative income of the residents because all chosen sites were considered to serve "low- to middle- income" households. Additionally, the authors found that site accessibility, measured as the average walking distance from each site to the nearest public transportation facility, had little to no influence on trip generation rates; this may be related to limited variation in transit access in extremely high-density residential estates of Hong Kong.

Under current approaches, the burden of parking infrastructure costs is often transferred to rental tenants (Rowe et al. 2014), and space and funds dedicated to parking limit the availability of affordable housing in urban contexts with a variety of accessible transportation options (Rogers et al. 2016). Developer relief (e.g., funds dedicated to motorized vehicle-based mitigations) could be rerouted to provide more affordable housing units or support non-motorized vehicle transportation modes. This could allow for an increase in affordable housing stock that provides safe, convenient transportation choices to people of limited means. More research would be required to fully understand and assess how decreased impact and mitigation fees might affect affordable housing availability.

Previous studies have provided comprehensive reviews of trip generation analysis methods, travel behavior, and the built environment, including a literature review by Ewing and Cervero (2010) and a review of tools to measure relationships by Handy et al. (2013). More recently, Currans (2017) provided a summary and critique of trip generation data and methods from a US-perspective, whereas de Gruyter (2019) offered an international one. All of these reviews note the importance of incorporating vehicle parking supply and pricing policies in estimates of vehicle demand, and that few existing approaches actually control for parking supply or management efforts in their models.

The current study helps fill these critical gaps by collecting new development-level data across urban areas, specifically at subsidized affordable housing developments. Furthermore, we directly estimate both vehicle and person trip activity, and incorporate controls for vehicle parking supply. The outlined methods and findings provide much-needed guidance for the application of trip generation analysis for affordable housing specifically, in line with local planning practices.

## DATA

This section describes the original data collection of motorized vehicle and person trip counts at 26 subsidized affordable housing locations in Los Angeles and the San Francisco Bay Area during the summer and fall of 2017. First, we describe our sampling strategy and site selection and recruitment process. Second, we present our data collection protocols—largely following the state-of-the-practice trip generation methods outlined in the 3rd Edition ITE *Trip Generation Handbook* (2014). Third, we define and describe secondary data used to control for site and built environment characteristics. Finally, we discuss externally collected and archived data used for validating the analysis. TABLE 1 provides statistical summaries of both the original data collection and validation dataset.

**TABLE 1 Summary Statistics for Original Data Collection Sites and Validation Sites**

| Trips per Occupied Dwelling Unit | Original Data Collection Sites (N: 26)[b] Mean | (Min, Max) | Validation Sample Los Angeles' Affordable Housing Trip Generation Study Sites (N: 9)[c] Mean | (Min, Max) |
|---|---|---|---|---|
| AM Peak Period (between 7:00-10:00AM)[a] | | | | |
| Motorized Vehicle Trip Rate | 0.53 | (0.10, 1.35) | 0.44 | (0.24, 0.63) |
| Person Trip Rate | 1.57 | (0.32, 2.87) | --- | --- |
| PM Peak Period (between 4:00-7:00AM)[a] | | | | |
| Motorized Vehicle Trip Rate | 0.40 | (0.11, 0.78) | 0.31 | (0.14, 0.43) |
| Person Trip Rate | 1.25 | (0.37, 2.97) | --- | --- |
| **Natural Log (LN) of Trip Counts** | | | | |
| AM Peak Period (between 7:00-10:00AM)[a] | | | | |
| LN(Motorized Vehicle Trips) | 3.48 | (2.49, 5.08) | 2.89 | (2.20, 3.66) |
| LN(Person Trips) | 4.56 | (3.33, 5.65) | --- | --- |
| PM Peak Period (between 4:00-7:00AM)[a] | | | | |
| LN(Motorized Vehicle Trips) | 3.22 | (2.64, 4.50) | 2.55 | (1.95, 3.26) |
| LN(Person Trips) | 4.34 | (3.43, 5.52) | --- | --- |
| **Site Characteristics** | | | | |
| Dwelling Units[d] | 73.0 | (23.0, 121.0) | 45.4 | (20.0, 80.0) |
| Average Square Footage (SQFT) of Units (in 1,000s of SQFT)[d] | 1.02 | (0.33, 1.43) | 1.04 | (0.75, 1.37) |
| Parking Ratio (Spaces to Total Units)[d, e] | 1.4 | (0.6, 2.9) | 1.2 | (0.4, 2.2) |
| **Built Environment & Location** | | | | |
| Population Density[f] (residents per acre) | 30.2 | (3.1, 176.7) | 40.7 | (8.0, 155.0) |
| Employment Density[g] (jobs per acre) | 27.0 | (1.0, 273.4) | 21.0 | (1.0, 85.0) |
| Retail Employment Density[h] (jobs per acre) | 1.8 | (0.0, 9.4) | 1.3 | (0.0, 7.4) |
| Jobs Accessible by 30-minute Transit Ride (in 10,000 jobs)[i] | 16.5 | (0.6, 56.1) | 21.5 | (1.5, 51.0) |

**Notes**:
[a] Peak period defined as peak period of the adjacent street, as per ITE.
[b] Trip Rate Data Source: Original data collection
[c] Trip Rate Data Source: (Fehr & Peers 2017)
[d] Source: Site managers/ developers and property records searches
[e] Source: Research team on-site data collection
[f] Source: 2016 ACS (5-year) B01003 Total Population (block group); Divided by Census Block Group area (acres)
[g] Source: 2015 LEHD Workplace Area Characteristics (WAC) All Jobs (JT00), Total Jobs (S000), Total Number of Jobs (C000); Divided by Census Block Group area (acres)
[h] Source: 2015 LEHD Workplace Area Characteristics (WAC) All Jobs (JT00), Total Jobs (S000), Total Number of Jobs by NAICS 44-45 "Retail" (CNS07); Divided by Census Block Group area (acres).
[i] Source: Processed by University of Minnesota's Accessibility Conservator using LEHD information, OpenStreetMap extracts, and the General Transit Feed Specification (GTFS) developed by Google, Inc. Accessibility data can be retrieved here: (Owen and Murphy 2018). Full documentation can be found here: (Owen, Murphy, and Levinson 2017).
---: Data were not collected and therefore summary is not applicable.
The measures described here summarize those that were retained during analysis. Additional measures such as intersection density, average number of bedrooms per unit, and distance to schools were tested but not included in the discussion due to lack of significance or inconsistent findings.

**Site Selection**

Candidate affordable housing sites within the main regions of interest (Los Angeles and the San Francisco Bay Area) were initially identified by referencing a list of California Tax Credit Allocation Committee (TCAC) program sites. We restricted our sample frame to those residential sites that offered 100% income-restricted housing (no mixed-income or mixed-use developments) that was “open to all” (e.g., units not reserved for specific populations with special needs), with parking bundled in residents’ rental payments.

Furthermore, we aimed to restrict our study locations to developments that served populations with similar incomes and controlled for differences between regional rental markets. The US Department of Housing and Community Development (HUD) defines affordable housing as income-restricted housing to support low-income households, as determined by median family income for a geographic area, which prevents households from paying more than 30% of their income for gross housing costs, including utilities (US Department of Housing and Urban Development 2019). Subsidized units are considered below market rate (BMR) and HUD determines applicant eligibility for its assisted-housing programs by establishing annual qualifying income limits. The median income across California’s fifty-eight countries varies widely, as do these income limits. In Los Angeles County, for instance, the 2015 area median income (AMI) for a family of four was $64,800 whereas it was $103,300 in San Francisco County. Potential study sites were restricted to those that serve households making between 50% and 60% below AMI. However, households that fell below the 50% AMI could still qualify for housing in these sites although they may not be able to afford them. In addition,some sites may also reserve a few dwelling units for households as low as 30% AMI and a few units for households as high as 80% AMI. Income of individual residents was not collected as part of our transportation impact study; instead, it was the classification of the development’s affordability qualifications that was used for site selection.

Sites meeting these criteria were geocoded using ArcGIS and then intersected with place types developed in precedent trip generation research (Howell et al. 2018) to inform how sites were located across different urban contexts. As mentioned previously, many existing trip generation data focus on suburban place types. However, as the current study proposes to increase data for urban areas, the sampling strategy emphasized urban locations (urban core, district, or neighborhoods) with a desire for roughly equivalent sites sampled in either Los Angeles or the San Francisco Bay Area.

One of the most constraining factors in site selection for any trip generation study is the process of contacting developers and/or site managers to be granted permission to access the site for observation. Developing a relationship with site managers and property owners also allowed for more detailed information about each site, such as parking supply and residential demographics.

Members of the research team visited each potential data collection site with the property staff in early June 2017 to discuss site characteristics and ensure the locations met the standards described in this section. In all, 26 locations selected for observation (see FIGURE 1).


**FIGURE 1 Study sites across: (left) Los Angeles and (right) San Francisco Bay Area**

## Person and Motorized Vehicle Trip Generation Data Collection

We collected person and motorized vehicle trip generation counts at 26 sites in Los Angeles (N: 15) and the San Francisco Bay Area (N: 11) during three data collection time periods: August 22-24 and 29-31, 2017 and October 11-12, 2017. For each site, trip counts were collected during the AM and PM peak periods of adjacent street traffic (7:00AM to 10:00AM and 4:00PM to 7:00PM) on Tuesdays, Wednesdays, or Thursdays. The data collection protocols reflect the guidelines presented in ITE's 3rd edition *Trip Generation Handbook* (Institute of Transportation Engineers 2014) and are documented in full in the corresponding project report (Clifton et al. 2018). Data were not collected on days that rained or coincided with events that may drive abnormally high or low peak periods, such as adjacent construction (roadway or development), nearby sports or arts events, or special events held at the development itself (e.g., special meetings, job interviews). Note that most developments were nearly 100% occupied.

Counts were collected manually through visual observation and inspection by individuals contracted through a temporary worker agency and trained by members of the research team (who were also present during data collection). In this approach, vehicle and person trips coming and going from the development were counted per 15-minute increments during each peak hour. These counts were then processed into peak hour counts using the ITE approach and data submission guidelines (Institute of Transportation Engineers 2014b). This approach is summarized in the following three steps:

A. Summarize entire site count information for 15-minute time increments (e.g., 7:00-7:15 AM, 7:15-7:30 AM);
B. Sum counts into moving hourly periods (e.g., 7:00-8:00 AM, 7:15-8:15 AM, 7:30-8:30 AM);
C. Determine the moving hourly period (i.e., the period with the greatest sum from B.) for both AM peak and PM peak for each development.

This process was completed both for person trip counts and motorized vehicle trip counts for each study site.

## Built Environment Measures

As mentioned previously, mode choices, travel distances, and trip frequency are influenced by the characteristics of the urban context in which travel takes place. Information on additional measures describing the sites' built environment and development characteristics were collected from developers and/or the site managers and archived spatial data. For this reason, the built environment characteristics described in TABLE 1 were considered in the analysis based on the relationships with varying motorized vehicle and/or person travel activity identified in the literature.

# METHODS

## Regression Analysis of Count Data

First, we transformed motorized vehicle and person trips (each for the AM and PM peak hour) using the natural log and regressed this upon the development and built environment characteristics around the site listed in TABLE 1. The transformation allowed for an ordinary least squares (OLS) linear regression analysis to be conducted to build the trip generation model. Because of the low sample size and behavior-based outcomes of this analysis, we denote marginal significance (p-value < 0.2) in all regression tables.

ITE's standard univariate regression model forms examine "trips" or the "natural log of trips" relative to the number of occupied dwelling units. In this analysis, we controlled for the count-based nature of the data by transforming the trips by using the natural log. Each estimated coefficient, $\beta_x$, can be interpreted as the expected percent change in trips for each incremental unit increase of the dependent variable. For simplicity of interpretation, we have also included the point elasticity in the regression outputs, which expresses the percent change in trips for each 1% increase of each dependent variable. An elasticity nearing +/- 1% suggests a more elastic relationship between the independent and dependent variables (larger effect size), while elasticities closer to 0% are indicative of less elastic relationships (smaller effect size).

It is worth mentioning that we estimated and tested alternative count-based model forms (such as negative binomial and Poisson). While the outcomes (in terms of coefficient direction and significance and model performance) were relatively similar to the models presented in this paper, the count-based models often performed worse in the predictive exercises, underestimating travel demand in many cases. These alternative models are not presented in this paper.

We calculated the approximate contribution of each independent variable in explaining the variation of trip generation for each model to explore the importance of each variable in predicting trips. A higher level of variation explained is an indication that the variable matters more for the given model. To approximate the contribution of variation explained, we estimated the regression with and without each independent variable. Then we compared the adjusted $R^2$ (explanation of variance, controlling for sample size) of the new model without the given variable with the adjusted $R^2$ for the model including all variables. We repeated this process for each model and variable to derive the estimates provided in the following section.

Due to the small sample size, multiple approaches were taken to explore the influence of individual sites and variables on model results. The outlier test for 'student residuals' (Neter, Wasserman, and Kutner 1989) identifies potential development outliers on the dependent variables. The Mahalanobis test (Tabachnick and Fidel 1989) examines multivariate outliers on the suite of independent variables (e.g., developments that *looked* different based on the suite of X-variables used). Cook's distance identifies any potentially influential cases (values greater than 2.5) (Bollen and Jackman 1985). The variance inflation factor (VIF) identifies any issues with multicolinearity (Neter, Wasserman, and Kutner 1989). We inspected the residual plots, such as histograms, boxplots, and quartile-quartile plots for normality, homoscedasticity, or other observations. We also employed the Shapiro-Wilk test for normality (Shapiro and Wilk 1965) on the residuals of estimated models and the Wu-Hausman tests for endogeneity (Nakamura and Nakamura 1998) to determine if any independent variables were correlated with residuals for different model forms. Additionally, the final regressions were re-estimated with and without each individual site (N=26) to explore the sensitivity of each estimated coefficient. Significant or notable findings from these tests are provided as appropriate. While no sites were removed from this analysis, the findings from these tests can help interpret which variables are likely to be the most important and consistent for prediction of site-level impacts.

**Validation of Regression Analysis**

The diagnostics tests described in the previous subsection explore the consistency and interpretability of the regression results. Because these models tend to be used predictively in practice, additional tests were considered using an externally collected validation dataset—motorized vehicle trip generation data at comparable affordable housing sites collected in Los Angeles in spring and fall 2016 (Fehr & Peers 2017). First, the models were used to predict motorized vehicle trips for the validation dataset. Observed versus predicted motorized vehicle trips were compared. Next, the original collected data and the validation data were pooled and the models were re-estimated. This pooled model allows for further exploration of the strength of each independent variable in predicting trip generation. No externally collected datasets were identified for validating the person trip generation models at affordable housing sites.

## RESULTS & DISCUSSION

The results for this analysis are presented in four subsections. First, motorized vehicle and person trip generation rates for our original data collection, as well as the validation dataset, are compared against the conventional approach for estimating residential trip generation rates. Second, the regression modeling results of the original dataset are provided. Third, the validation of the modeling results, as well as the re-estimation of the models using pooled original and validation data, are presented. Fourth, the most important contributing predictors are identified in model form and the role of parking supply in motorized vehicle trip generation estimation is explored in more detail.

### Comparison of Observed Trip Rates with Conventional Rates and Validation Sample

While more detailed regression analysis was the focus of this manuscript, before exploring these findings we examine a simple comparison of motorized vehicle and person trips generated at observed sites compared with the conventional approach. Currently, the industry standard ITE *Trip Generation Manual* does not include any ‘subsidized affordable housing’ data. Practitioners may then rely upon the general ‘apartment’ code (Land Use Code 220), which represents market rate, single use developments with free and unconstrained parking located in areas with little-to-no access to transit, bicycle, or pedestrian facilities (i.e., suburban areas). The motorized vehicle trips generated at the sites collected in this study—as well as the validation sample (Fehr & Peers 2017)—are plotted against the AM and PM motorized vehicle trips provided by ITE’s 9$^{th}$ edition *Manual* (Institute of Transportation Engineers 2012)[1] in FIGURE 2 and FIGURE 3, respectively. The urban context designations originally developed for site selection as shown in FIGURE 1 and documented in (Clifton et al. 2018) are included in these figures to indicate relative location of sites across the study areas.

Although the motorized vehicle trip rates from this study tend to be slightly below (AM peak) and largely below (PM peak) the ITE average apartment trip rates, it is difficult to discern a pattern of variation when looking at the differences in trip rates by urban place types. By inspection, the validation sample tends to track closely to the data collected in this study. These findings suggest that subsidized affordable housing developments, which are generally in more urban and transit-adjacent contexts, are more likely to have lower motorized vehicle trip generation rates than market rate suburban sites (i.e., ITE), particularly in the PM peak hour. In other words, market rate multifamily apartment data from suburban contexts should not be used to approximate transportation impacts at subsidized affordable housing sites in most urbanized areas with proximity to transit. However, it is not clear from these comparisons whether the differences observed are driven by the comparison of urban versus suburban contexts, by the

[1] The Institute of Transportation Engineers has since published a 10$^{th}$ edition *Manual* which revised many of the land use codes. As part of this revision, the residential land use code 220 Apartments was removed as the intensity of the sites were not identified. Where information was available, these data were absorbed into the subsequent multifamily residential codes which specify intensity of development (e.g, high-, mid-, and low-rise).

comparisons of market rate versus subsidized, or by some combination of urban contexts and affordability.

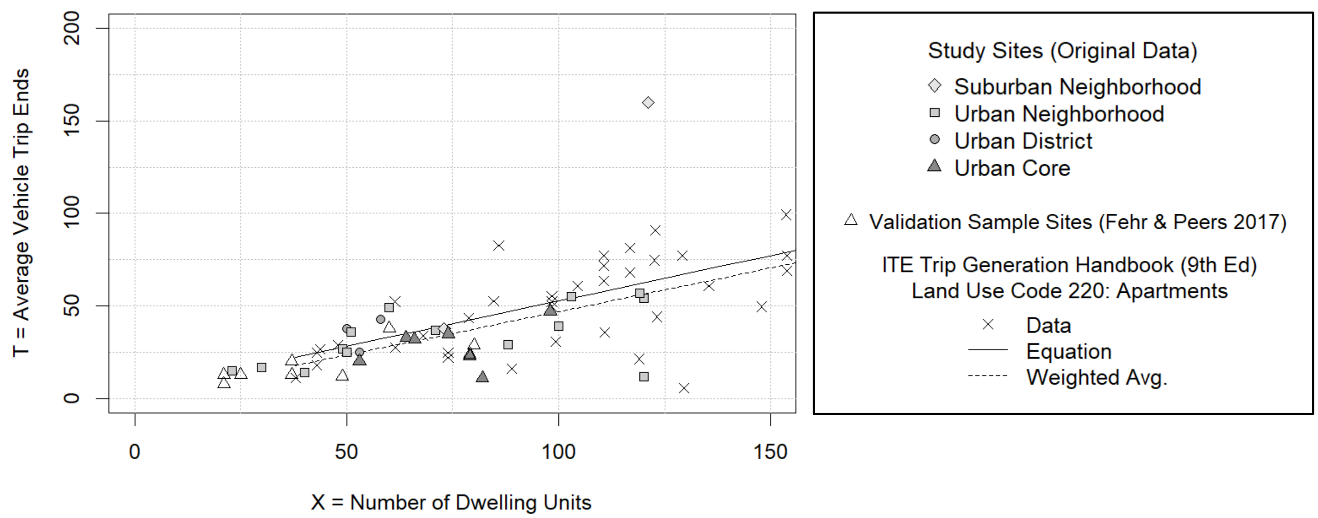


**FIGURE 2 Comparison of AM Peak Hour of Adjacent Street Motorized Vehicle Trips**

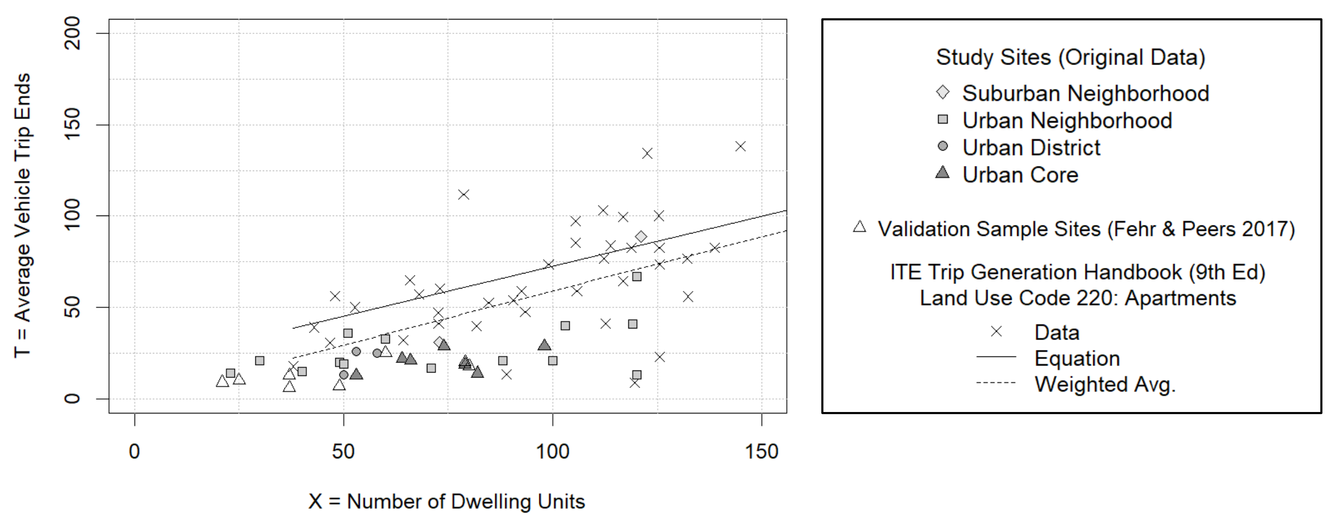


**FIGURE 3 Comparison of PM Peak Hour of Adjacent Street Motorized Vehicle Trips**

Historically, motorized vehicle trips generated have been the center of attention in transportation impact analyses. However, the industry standard has begun shifting the focus toward overall person activity (person trip generation rates). This shift will enable practitioners and agencies to consider the activity rates of people—not just cars—which can then be divided into modes based on the urban contexts or built environment in the surrounding areas. In response to this, ITE published guidance for approximating person trip rates for land uses where person trip data are not available (Institute of Transportation Engineers 2014). ITE's suburban motorized vehicle trip counts (called 'baseline' sites) are converted into approximated person trip counts using motorized vehicle mode share and motorized vehicle occupancy rate information. This information is either based on real data collected at comparable ‘baselines’ sites or derived from assumptions based on the known context of the sites. Because there is no industry standard person trip data available for comparison, we plot the data collected in our study against the industry’s approach for approximating person trips generated (see FIGURES 4 and 5 for the AM and PM peak hours, respectively).

We find that the industry-standard approach for approximating person trips generated drastically underestimates the person trip activity at our observed sites, especially for the AM peak hour. While ITE does not publish site-level information that allows us to explore why this may be the case, we have a few hypotheses. The ‘baseline’ sites are generally representative of highly suburban areas with little to no biking, walking, or access to transit, and with free and unconstrained parking (Institute of Transportation Engineers 2014). Urbanized areas with higher destination accessibility are more likely to encourage frequent pedestrian trips nearby and subsequently are likely to facilitate person trip activity in general. In other words, areas with more opportunities may spur more site-level activity (trips generated). In the ‘baseline conversion’ approach to estimating person trip generation behavior, we also assume that the motorized vehicle mode shares and motorized vehicle occupancy rates are fairly low because the baseline sites are assumed to be almost entirely car-oriented. However, in a 2012 study of restaurants and convenience market locations, non-motorized vehicle mode shares of approximately 30% on average were observed at suburban sites closely aligned with ITE’s definition of baseline (Clifton, Currans, and Muhs 2012). While it may be tempting to assume motorized vehicle-oriented development will only attract motorized vehicle traffic, observations tend to suggest otherwise.

The following subsection explores a more rigorous analysis of the predictors of motorized vehicle and person trip generation behavior observed at our study sites.

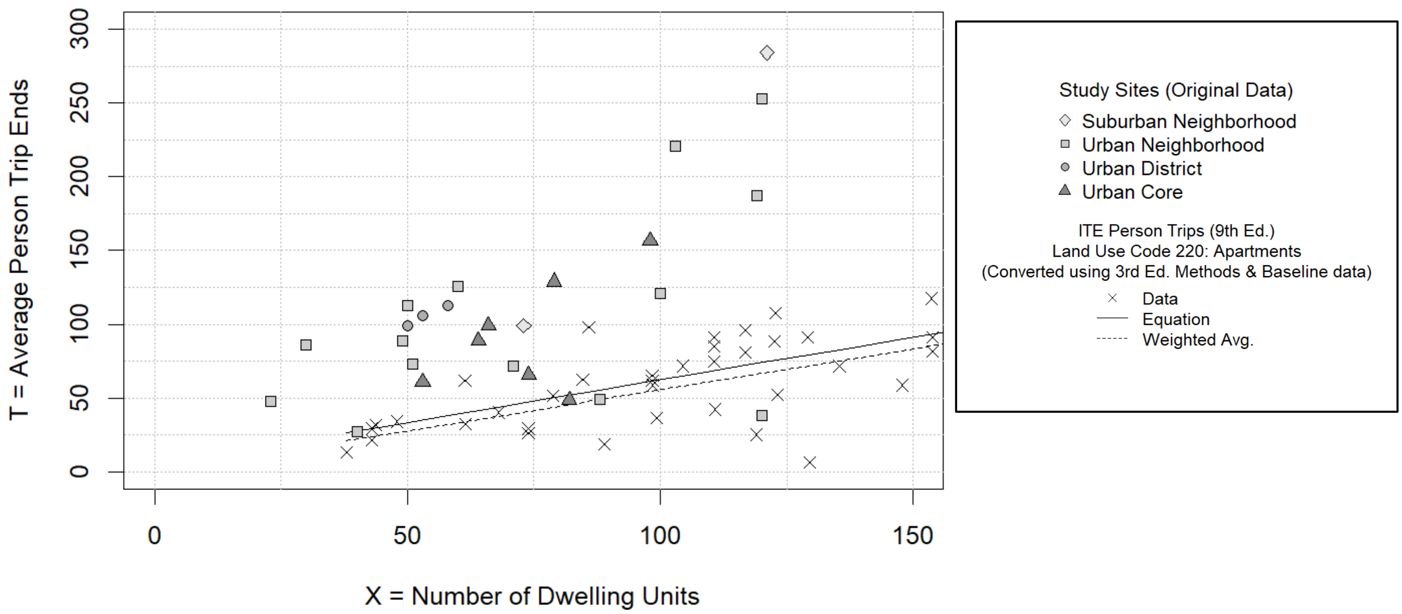


**FIGURE 4 Comparison of AM Peak Hour of Adjacent Street Person Trips**

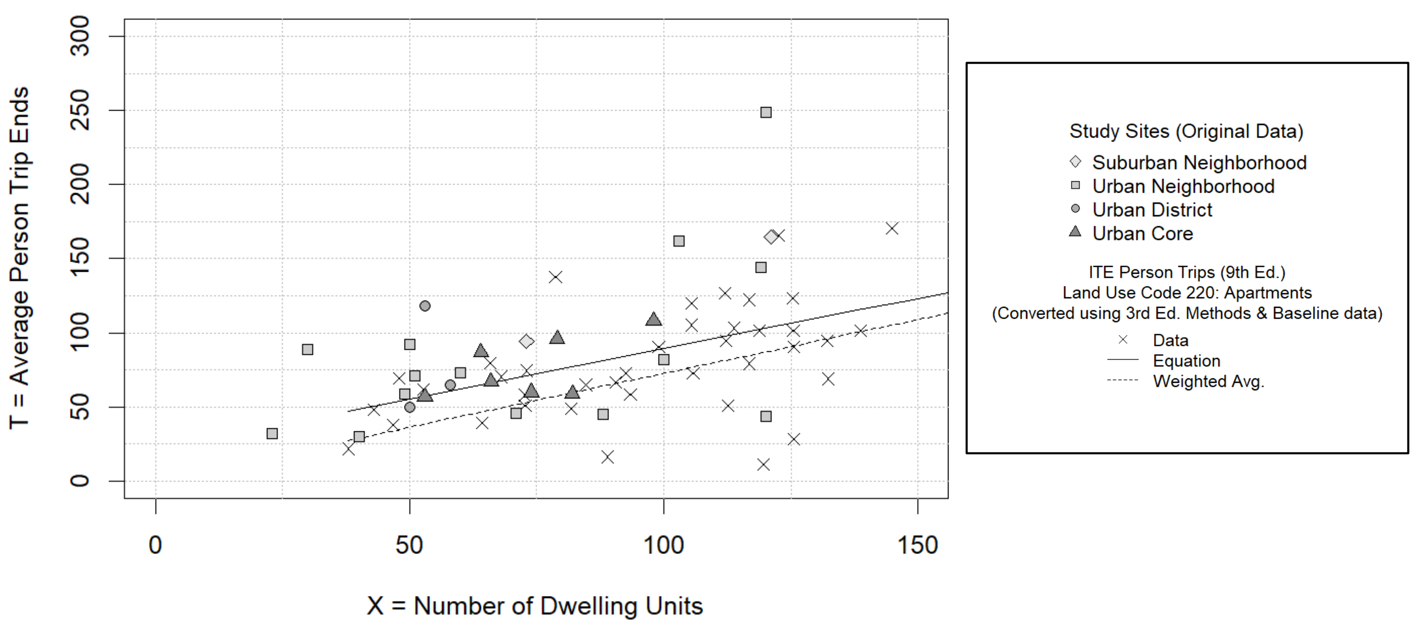


**FIGURE 5 Comparison of PM Peak Hour of Adjacent Street Person Trips**

### Model Regression and Validation Results

This subsection presents the regression model results for our original data collection. A more comprehensive interpretation and discussion of findings across the full analysis (regression, validation) is provided in the Discussion section. The results of the OLS linear regression estimating motorized vehicle and person trips generated for AM and PM peak hour are provided in TABLE 2. In TABLE 3, we explore the contribution of each independent variable toward explaining the overall variance in the models. The models estimated in TABLE 2 are provided in this table, as are the subsequent models estimated by pooling the original study data with the validation sample (presented further in the following sub-section).

Overall, the development of the presented models was the result of iterative estimation, tests, and checks on the performance and predictive power of the model. Checks on performance included explanation of variance, significance, and interpretability, checks on assumptions, checks on outliers, and their contribution to driving coefficients into significance or not, and checks on prediction included validation, bias, and accuracy. Based on the tests discussed in the methods section, we found by and large that a transformation of the count-based dependent variables was necessary (compared with linear relationships) and that the models were not further improved by count-specific methods (e.g., negative binomial, Poisson). Because of this, the simpler form (OLS) was chosen. Furthermore, the transformation of the dependent variable significantly improved the normality checks on regression assumptions, as well as the predictive power of estimates. The presented models show no significant violations on normality, but with low sample size, a few sites with higher than expected trip rates tended to drive the significance of a few variables. Those cases are described in the context of the interpretation of variables below.

Site characteristics that describe the number of dwelling units, average dwelling unit square footage, and the parking supply are all significant and positive predictors of motorized vehicle and person trips in the AM peak hour. In the PM peak hour, there was not enough evidence to suggest that the average size of dwelling units significantly predicted motorized vehicle trips. This finding may be an artifact of the tendency for the AM peak hour to be less likely to ‘spread’ across the time period, making the AM peak period more dependent on the number of people across each dwelling. In other words, the time for work or school to begin is more fixed than the time for work or school (or other activities) to end. These results suggest that site characteristics (dwelling units, average square footage of dwelling units, and parking supply) are the largest contributors to the overall explanation of variance (see TABLE 3). Not surprisingly, for all models, the number of dwelling units—a proxy for the number of households living in each development—contributed the most to explaining variance. Controlling for parking supply also aids in explaining variation in motorized vehicle trip generation. Although parking supply was marginally significant in explaining AM peak hour person trips, the sensitivity tests suggest that this significance was driven by one or two sites with a high level of parking supply and substantially higher person trip rates. For person trip generation, a large amount of variation is explained by the average size of the dwelling unit. While not typically collected in transportation impact studies of multifamily residential developments, average dwelling size may act as a proxy for household size, thus capturing more variation in the total amount of person trip activity at multifamily sites.

There was less evidence across all models to correlate the built environment with motorized vehicle or person trips. Population density was only marginally significant in predicting motorized vehicle trips. Although employment density was significant across all four models, subsequent sensitivity tests point toward one or two sites with extremely high employment density driving the significance (but not the coefficient effect size) of these findings. This suggests that the coefficient is relatively stable, but there was not enough evidence or information to suggest it was a significant predictor. In more recent years, the built environment has largely been the focus of larger trip generation studies (Schneider, Shafizadeh, and Handy 2015; Clifton, Currans, and Muhs 2012; Dock et al. 2015; C. de Gruyter 2019). While there is evidence to suggest motorized vehicle trip rates tend to be lower in more urban areas, these findings suggest that parking supply may be a more important variable in more accurately estimating motorized vehicle trip generation rates (see TABLE 3). While explaining less variance, retail employment density was a significant and positive predictor of person trip behavior during the AM and PM peak period. This may suggest that residential locations with more intense proximity to retail destinations may generate more person-activity to and from the development.

Initial iterations of this analysis controlled for proximity to transit in terms of distance to transit, as often included in multifamily trip generation studies. However, location requirements for subsidized affordable housing developments often require or encourage meeting some minimum standards for transit access, which resulted in limited variation of the distance to transit across study sites. To improve this measure, we incorporated a measure of transit accessibility in terms of jobs accessible within a 30 minute transit ride (Owen, Murphy, and Levinson 2017). However, sensitivity tests indicate this marginal significance may be driven by one or two sites acting as outliers, making the interpretation of this coefficient problematic.

**TABLE 2 Regressions of AM and PM Peak Period Motorized Vehicle and Person Trips**

| | AM Peak Period | | | | | | | | PM Peak Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Motorized Vehicle Trips** ***[ Transformation: ln(X+1) ]*** | | | | **Person Trips** ***[ Transformation: ln(X+1) ]*** | | | | **Motorized Vehicle Trips** ***[ Transformation: ln(X+1) ]*** | | | | **Person Trips** ***[ Transformation: ln(X+1) ]*** | | | |
| | Coef | Elasticity | p-value | | Coef | Elasticity | p-value | | Coef | Elasticity | p-value | | Coef | Elasticity | p-value | |
| Constant | 1.45 | --- | <0.01 | *** | 2.17 | --- | <0.01 | *** | 1.65 | --- | <0.001 | *** | 2.34 | --- | <0.001 | *** |
| **Site Characteristics** | | | | | | | | | | | | | | | | |
| Total Dwelling Units | 0.01 | 0.75 | <0.01 | *** | 0.01 | 0.79 | <0.01 | *** | 0.01 | 0.65 | <0.01 | *** | 0.01 | 0.79 | <0.01 | *** |
| Square Footage of Dwelling Unit (in 1,000 SQFT) | 0.54 | 0.55 | 0.09 | * | 1.10 | 1.13 | 0.03 | *** | 0.28 | 0.29 | 0.27 | | 0.89 | 0.91 | 0.01 | ** |
| Parking Ratio (Spaces to Total Units) | 0.55 | 0.78 | <0.01 | *** | 0.29 | 0.41 | 0.08 | * | 0.50 | 0.70 | <0.01 | *** | 0.17 | 0.24 | 0.30 | |
| **Built Environment & Location** | | | | | | | | | | | | | | | | |
| Population Density (residents per acre) | -0.002 | -0.07 | 0.36 | | 0.001 | 0.03 | 0.75 | | -0.003 | -0.10 | 0.13 | + | 0.002 | 0.07 | 0.44 | |
| Employment Density (jobs per acre) | -0.005 | -0.14 | <0.01 | *** | -0.005 | -0.14 | <0.01 | *** | -0.003 | -0.08 | 0.04 | * | -0.003 | -0.09 | 0.08 | * |
| Retail Employment Density (jobs per acre) | -0.001 | 0.00 | 0.97 | | 0.070 | 0.13 | 0.03 | ** | -0.014 | -0.03 | 0.55 | | 0.058 | 0.11 | 0.07 | * |
| Jobs Accessible by 30-minute Transit Ride (in 10,000 jobs) | 0.010 | 0.17 | 0.11 | + | 0.003 | 0.05 | 0.66 | | 0.008 | 0.13 | 0.13 | + | -0.001 | -0.02 | 0.87 | |
| Observations | 26 | | | | 26 | | | | 26 | | | | 26 | | | |
| $R^2$ | 0.75 | | | | 0.72 | | | | 0.75 | | | | 0.64 | | | |
| Adjusted $R^2$ | 0.65 | | | | 0.61 | | | | 0.66 | | | | 0.50 | | | |
| Residual Std. Error (df) | 0.33 (18) | | | | 0.35 (18) | | | | 0.28 (18) | | | | 0.35 (18) | | | |
| F Stat (df) | 7.68 (7; 18)*** | | | | 6.52 (7; 18)*** | | | | 7.88 (7; 18)*** | | | | 4.62 (7; 18) | | | |

**Notes**:
Model form: Ordinary Least Squares (OLS)
All outcomes are transformed using the natural log (ln) of the variable + 1.
***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10; + : p-value < 0.20.

**TABLE 3 Contribution of Variables to Explaining Variance from the Models Presented in TABLE 2**

| **Peak Period:** | **AM** | | | **PM** | | |
|---|---|---|---|---|---|---|
| **Trip Rate Model:** | **Motorized Vehicle** | | **Person** | **Motorized Vehicle** | | **Person** |
| **Sample:** | Original | Pooled | Original | Original | Pooled | Original |
| **Site Characteristics** | | | | | | |
| Dwelling Units | 0.31 | 0.39 | 0.34 | 0.33 | 0.37 | 0.43 |
| Square Footage of Dwelling Unit | 0.04 | 0.03 | 0.23 | *n.s.* | *n.s.* | 0.18 |
| Parking Ratio (Spaces to Total Units) | 0.25 | 0.14 | 0.05 | 0.28 | 0.16 | *n.s.* |
| **Built Environment & Location** | | | | | | |
| Population Density | *n.s.* | *n.s.* | *n.s.* | 0.03 | *n.s.* | *n.s.* |
| Employment Density | 0.16 | 0.04 | 0.15 | 0.07 | *n.s.* | 0.06 |
| Retail Employment Density | *n.s.* | *n.s.* | 0.09 | *n.s.* | *n.s.* | 0.07 |
| Jobs Accessible by 30-minute Transit Ride | 0.03 | *n.s.* | *n.s.* | 0.03 | *n.s.* | *n.s.* |

**Notes**:
"Original" refers to the original data collection presented in this paper. "Pooled" refers to the pooled sample that contains the original data collection presented in this paper as well as the validation sample collected in LA.
Values indicate the change (increase) in the explanation of variance (adjusted $R^2$) before and after each variable is introduced *ceteris paribus*.
n.s.: Not significant (marginal significance $p < 0.2$)

## Validation and Pooled Model Testing

Two steps were completed in the validation process. First, the predictive power of the models presented in the previous subsection was tested using externally collected and comparable motorized vehicle trip generation counts at nine sites from Los Angeles (Fehr & Peers 2017). Second, our study's sample was pooled with this validation sample to test the consistency of model findings.

*Prediction versus Observation*

The motorized vehicle trip count models provided in the previous subsection (see TABLE 2) were used predictively to estimate motorized vehicle trip counts for each of the nine validation sites. The estimated motorized vehicle trip counts were plotted against the observed motorized vehicle trip counts (see FIGURE 6) from the external dataset (Fehr & Peers 2017). Only those variables that significantly (p-value < 0.1) predicted motorized vehicle trip rates were included in the predictive model. Because the significance of employment density was driven by one or two sites, this variable was excluded in the predictive models.

The diagonal line imposed on both graphics represents the point in which the predictive values would be equal to observed values. These findings suggest that the simplified AM peak hour model is a relatively good predictor for motorized vehicle counts. The PM peak hour model tends to underestimate motorized vehicle counts. Using only these predictors, the results suggest the models are accurate within a 25-34 percent difference between predicted and observed counts on average, calculated as follows:

$$Percent\ Difference = 100 * \frac{\sum_{i=1}^{N}\left(\frac{predicted_i - observed_i}{observed_i}\right)}{N}$$

where $N$ is the number of validation sites (N=9) and $i$ is the $i^{th}$ observation in the validation data set. If all coefficients from the models in TABLE 2 were used in the prediction regardless of significance, the models would tend to over predict motorized vehicle counts at the validation sites by approximately 60-65% for either peak hour. Relying on the significance and relevant coefficients from the pooled original and validation samples presented in the following section would reduce the percent difference to 17-18%.

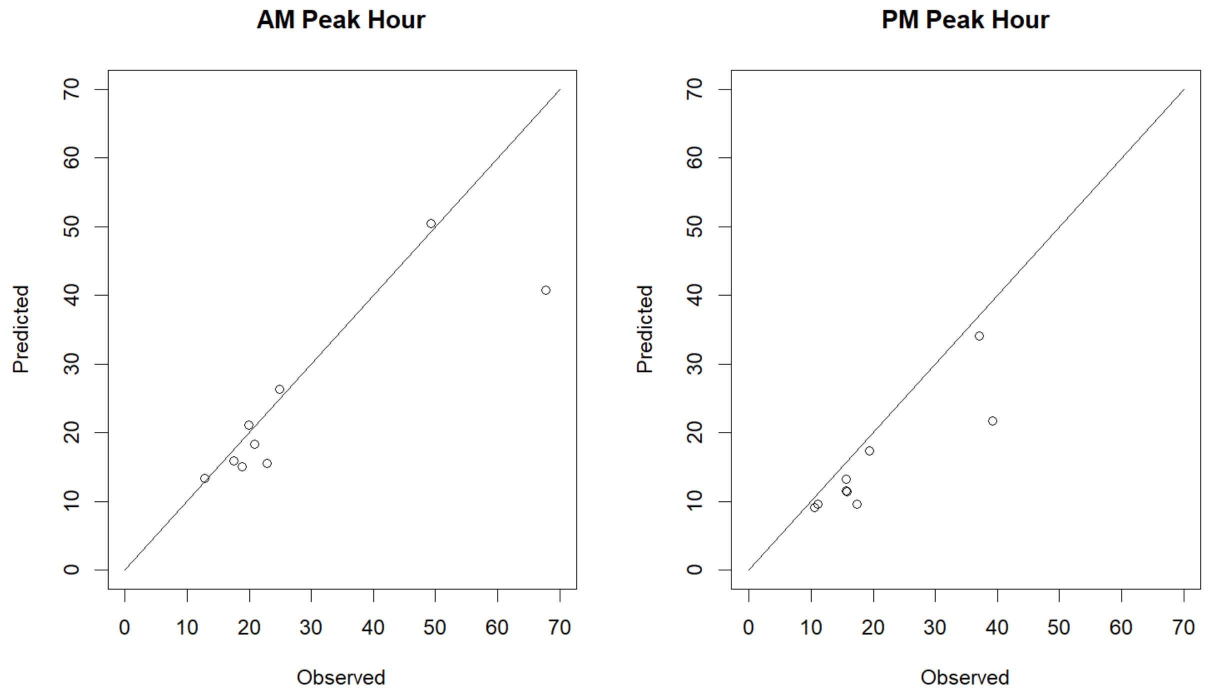


**FIGURE 6 Motorized Vehicle Trip Counts Predicited Using Original Studys Models (see TABLE 2) for Validation Sites (Fehr & Peers 2017) in the (left) AM peak hour and (right) PM peak hour**

*Pooled Model*

Following the validation, the original data collection and validation sample were pooled and the motorized vehicle trip count models provided in TABLE 2 were estimated using this pooled sample (see TABLE 4). The models estimated using the original sample are provided again in TABLE 4 to ease the comparison between the original and the pooled models. Based on the effect size, significance and contribution to explaining variance, the total number of dwelling units per development remains a strong predictor of motorized vehicle counts in both the AM and PM peak period. The effect size of parking supply (and corresponding elasticity and contribution to explained variance shown in TABLE 3) is reduced for both the AM and PM peak models, but the significance of this predictor is maintained. While the role of the average square footage of dwelling units remains approximately the same in the AM peak hour model, the effect size and significance of this variable in predicting PM peak hour motorized vehicle counts is increased in the pooled model. The addition of the nine externally collected sites reduces the significance of all of the built environment variables, supporting the indications that the significance of these factors may have been driven by one or two extreme cases.

**TABLE 4 Regressions of AM and PM Peak Period Motorized Vehicle Trips for (a) Original Sample and (b) Original and Validation Sample Pooled**

| | **AM Peak Period Motorized Vehicle Trips** *[ Transformation: ln(X+1) ]* | | | | | | | | **PM Peak Period Motorized Vehicle Trips** *[ Transformation: ln(X+1) ]* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Original Data Collection** (repeated from TABLE 2 to ease interpretation) | | | | **Pooled Sample (Original and Validation Samples)** | | | | **Original Data Collection** (repeated from TABLE 2 to ease interpretation) | | | | **Pooled Sample (Original and Validation Samples)** | | | |
| | Coef | Elasticity | p-value | | Coef | Elasticity | p-value | | Coef | Elasticity | p-value | | Coef | Elasticity | p-value | |
| Constant | 1.45 | --- | <0.01 | *** | 1.402 | --- | <0.01 | *** | 1.65 | --- | <0.001 | *** | 1.334 | --- | <0.01 | *** |
| **Site Characteristics** | | | | | | | | | | | | | | | | |
| Total Dwelling Units | 0.01 | 0.75 | <0.01 | *** | 0.01 | 0.83 | <0.01 | *** | 0.01 | 0.65 | <0.01 | *** | 0.01 | 0.76 | <0.01 | *** |
| Square Footage of Dwelling Unit (in 1,000 SQFT) | 0.54 | 0.55 | 0.09 | * | 0.54 | 0.56 | 0.08 | * | 0.28 | 0.29 | 0.27 | | 0.40 | 0.56 | 0.14 | + |
| Parking Ratio (Spaces to Total Units) | 0.55 | 0.78 | <0.01 | *** | 0.45 | 0.61 | <0.01 | *** | 0.50 | 0.70 | <0.01 | *** | 0.45 | 0.61 | <0.01 | *** |
| **Built Environment & Location** | | | | | | | | | | | | | | | | |
| Population Density (residents per acre) | -0.002 | -0.07 | 0.36 | | -0.002 | 0.01 | 0.36 | | -0.003 | -0.10 | 0.13 | + | -0.004 | -0.03 | 0.59 | |
| Employment Density (jobs per acre) | -0.005 | -0.14 | <0.01 | *** | -0.003 | -0.06 | 0.06 | * | -0.003 | -0.08 | 0.04 | * | -0.005 | -0.03 | 0.26 | |
| Retail Employment Density (jobs per acre) | -0.001 | 0.00 | 0.97 | | -0.004 | -0.01 | 0.88 | | -0.014 | -0.03 | 0.55 | | -0.024 | -0.02 | 0.70 | |
| Jobs Accessible by 30-minute Transit Ride (in 10,000 jobs) | 0.010 | 0.17 | 0.11 | + | -0.000 | -0.01 | 0.95 | | 0.008 | 0.13 | 0.13 | + | 0.001 | 0.02 | 0.82 | |
| Observations | 26 | | | | 35 | | | | 26 | | | | 35 | | | |
| $R^2$ | 0.75 | | | | 0.70 | | | | 0.75 | | | | 0.71 | | | |
| Adjusted $R^2$ | 0.65 | | | | 0.63 | | | | 0.66 | | | | 0.64 | | | |
| Residual Std. Error (df) | 0.33 (18) | | | | 0.36 (27) | | | | 0.28 (18) | | | | 0.33 (27) | | | |
| F Stat (df) | 7.68 (7; 18)*** | | | | 9.163 (7; 27) *** | | | | 7.88 (7; 18)*** | | | | 9.62 (7; 27) *** | | | |

**Notes**:
Model form: Ordinary Least Squares (OLS)
All outcomes are transformed using the natural log (ln) of the variable + 1.
***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10; + : p-value < 0.20.

**Most Important Predictors**

The most important predictors of motorized vehicle and person trip counts are clarified here after considering the overall findings (e.g., significance, effect size and elasticity, contribution to explaining variation (adjusted $R^2$), validation findings (for motorized vehicle trip models only), and sensitivity of individual sites and/or variables). Based on these findings, the most important predictor variables were identified and incorporated into the following equations[2]:

$$Vehicle\ Trips_{AM} = \exp(1.45 + 0.01 * Dwelling\ Units + 0.54 * Square\ Footage + 0.55 * Parking\ Ratio) - 1$$

$$Vehicle\ Trips_{PM} = \exp(1.65 + 0.01 * Dwelling\ Units + 0.50 * Parking\ Ratio) - 1$$

$$Person\ Trips_{AM} = \exp(2.17 + 0.01 * Dwelling\ Units + 1.10 * Square\ footage\ in\ 1{,}000s + 0.07 * Retail\ Employment\ Density) - 1$$

$$Person\ Trips_{PM} = \exp(2.34 + 0.01 * Dwelling\ Units + 0.89 * Square\ footage\ in\ 1{,}000s + 0.058 * Retail\ Employment\ Density) - 1$$

Dwelling units is the most common conventional indicator for estimating transportation impacts of residential units based on industry approaches, e.g., (Institute of Transportation Engineers 2014). Like trip generation, the estimation of parking demand (and therefore parking supply needs) of new development is an essential step of evaluating the transportation needs at individual developments. However, there is strong evidence to suggest that unconstrained or free parking supply results in increased motorized vehicle demand, particularly at residential locations, e.g., (Chatman 2013; Shoup 2003; 2017; Arrington and Cervero 2008). Yet, parking supply is rarely incorporated into the estimation of vehicular use. The determination of parking supply for new development is typically based on an entirely separate database and estimation process (Hooper 2019). In this study, we find both positive and strong significance in the relationship between the average parking supply at affordable housing developments and the motorized vehicle trip generation use, controlling for the built environment as well as the average dwelling size of developments. This indicates that the off-street parking supply on site relates to an increase in motorized vehicle trip counts (and likely motorized vehicle miles traveled). In other words, parking supply should be incorporated into vehicle travel demand estimates.

To further explore the observed relationship of parking supply with predictions in motorized vehicle trips, we use the regression models provided in TABLE 2 to estimate the motorized vehicle trips per dwelling unit for varying hypothetical parking supply rates—all other variables taken at the average observed value. This reveals that an increase in parking supply from 1.0 to 2.0 parking spaces per dwelling unit would result in an increase of approximately 0.26 motorized vehicle trips per dwelling unit in the AM peak and 0.18 motorized vehicle trips per dwelling unit in the PM peak (see dotted lines and text in FIGURE 7). If one decreased the parking supply by the same margin, the effect would equal the same magnitude reduction in trips. Although these effect sizes appear to be small, the aggregate impact of an entire development could be significant. For example, a 100-unit development would see a reduction of

[2] Trip counts were transformed using a natural log. Although there were no sites observed that had 'zero' trips, this possibility of this occurring was accounted for using a 'ln(trips +1)' transformation. Predictively, this means we reduce the predicted counts by one after transformation occurs.

26 trips in the morning peak and 18 trips in the evening if the parking ratio was reduced by an average of 1 parking spot per dwelling unit. Taken over an entire neighborhood of similarly situated multifamily dwellings, the impact is even more pronounced.

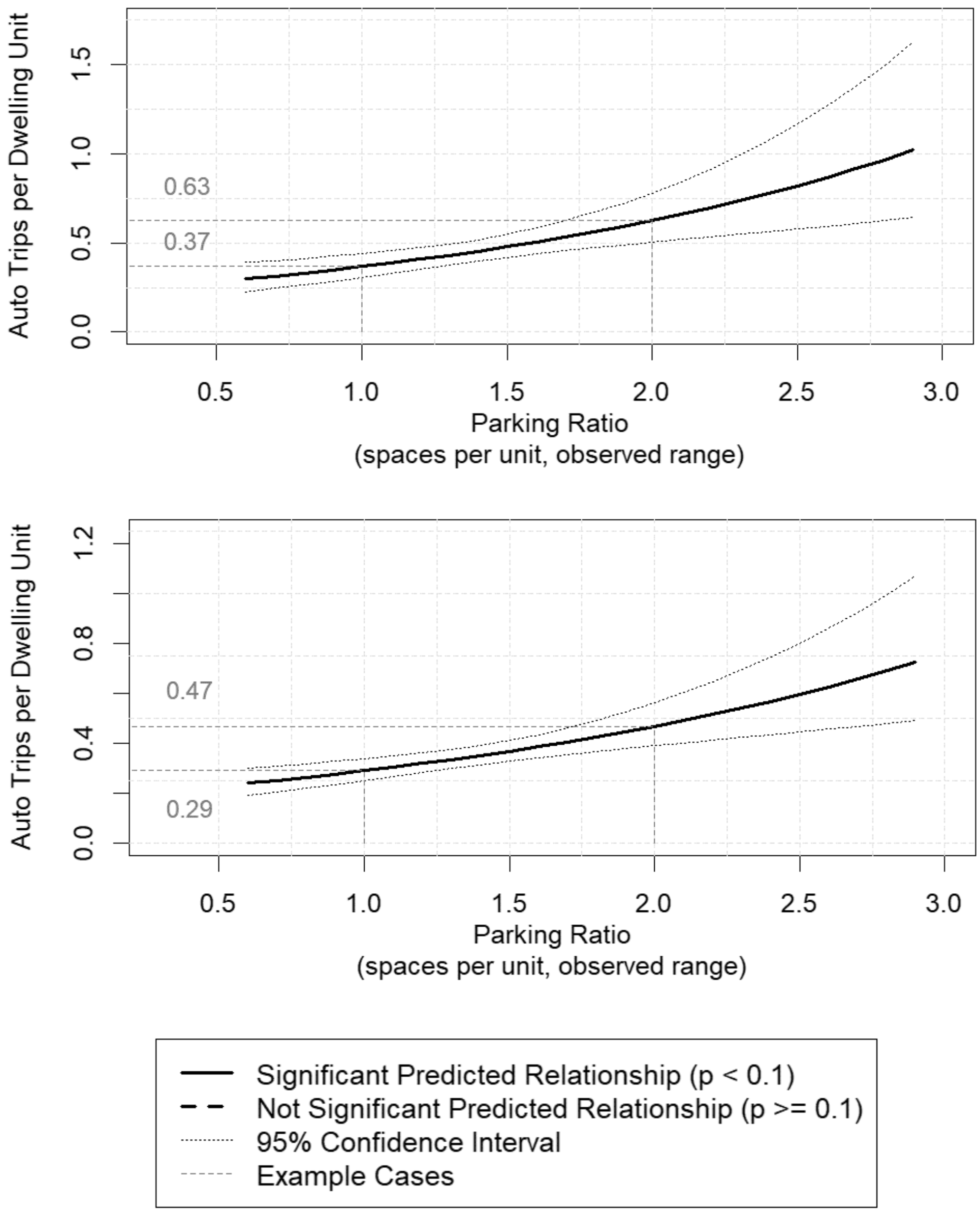


**FIGURE 7 Predicted Motorized Vehicle Trips per Dwelling Unit Across Varying Parking Supply Ratios (all other variables taken at the average observed values) for the (top) AM Peak Hour and (bottom) PM Peak Hour.**

## Limitations of Data Collection Protocols for Changing Transportation Landscapes

Looking forward into the transportation future, it is becoming apparent that survey methodologies for collecting count data, including those employed in this study, were ill-equipped to understand and approximate the impact related to transportation network companies

(TNCs). Specifically, motorized vehicle counts were explicitly defined as motorized vehicles that drove and parked on-site, as similar previous studies have considered. This implies that a "cordon" or boundary is defined around the development to distinguish "on-site" and all trips (person or vehicle) are captured once they cross the cordon. If motorized vehicles were parked on an adjacent site, picking up/dropping off individuals, or if a TNC service was used by a traveler observed, these behaviors were not reflected in the count data alone (unless the cordon line was crossed and the drop-off point was on-site). Some of this is captured by an intercept survey (not presented in this paper) with questions on the purpose of the trip (e.g., food delivery) and a TNC-sensitive mode choice (e.g., rideshare). However, the survey team noticed at some very urban locations that TNC and non-TNC vehicle trips coming to the development, but not crossing the cordon, would be conflated in the intercept survey protocols.

A protocol adjustment was tested on the second day of data collection where count staff were instructed to mark the number of people who got in or out of the motorized vehicle and the number of people who stayed in the motorized vehicle for any motorized vehicle parked adjacent or a pick up/drop off. This would enable the research team to identify if the trip made accounted for a parked motorized vehicle or drop off/pick up situation. This method did enable the team to capture more information for some of the sites, but we ultimately determined that the quality of the data was too inconsistent to be able to use in adjusting the vehicle count data. Based on transportation impact analyses that originated from a desire to quantify travel to and from a single parcel, accounting for TNC trips separately from person vehicle behavior poses a major limitation on the collection of count data in order to fully capture a split of motorized vehicle mode share types (e.g., personal motor motorized vehicle trip vs. TNC trip). In other words, conventional cordon-based approaches inhibit the ability to capture the impacts of travel to and from a specific development in cases where the traveler parked or was dropped off outside of the cordon. Improvements to the data collection protocols could enable site-level data to better inform other aspects of planning, including curb space management and development-level impacts on the surrounding neighborhood.

## CONCLUSIONS

This study contributes an original trip generation data collection and analysis of 26 subsidized affordable housing developments in the Los Angeles and San Francisco Bay Areas. We focused on subsidized affordable housing locations, which has helped push practice toward a greater understanding of how buildings oriented toward different economic markets impact transportation facilities differently.

The main findings suggest that parking supply, average size of development dwellings, and retail density are major contributors to capture variation in trip rates. These variables are not conventionally collected and controlled for in trip generation analyses, but this study suggests that these variables tend to be primary controls for understanding variations in residential (at least at affordable subsidized housing) trip generation rates. Inclusion of such variables in transportation impact analyses is a necessary improvement, given their contributions to travel.

A larger pool of localized data examining the relationship between parking and vehicle use may further confirm the positive link established by the literature for a given municipality. Such data would provide justification for policies aimed at restricting automobile use via parking pricing or supply restrictions in line with a city's emissions threshold targets or multimodality goals. While cities worldwide have had success in reductions of vehicle use out of parking policy schemes, parking policies should be careful not to exacerbate social inequities and unduly burden low-income households (Pitsiava–Latinopoulou et al. 2012). This work demonstrates how restriction of parking supply, for example, may deter vehicle use; however, policies for affordable housing should be implemented with caution and supplemented by policies to expand access to employment and necessary activities by other modes.

Both parking supply and average square footage of dwelling units may be considered additional proxies for household socio-economic and demographic characteristics. The parking supply is an indication of the availability of on-site parking for owned motorized vehicles. Not surprisingly, without additional supply, households make fewer motorized vehicle trips to and from the households in both the AM and PM peak periods. The average size of dwelling units in each development is a proxy for how many individuals are in each household; the more space, the more individuals live in each household, and the more they travel to and from the development. The findings from this study emphasize the importance of incorporating these site-level descriptive variables in transportation impact analyses. The inclusion of parking supply particularly is in line with calls for travel plans internationally to consider car parking management measures, and the observed relationship between parking supply and vehicle travel reiterates the need to do so (C. D. de Gruyter et al. 2018).

It is important to note that additional work is needed to strengthen the comparison between the impacts of behavior at market rate and subsidized developments. While several market rate studies have been published recently, they have been limited to “Smart Growth” areas where the types of development tend to be more compact. We have shown in our analysis that the size of the dwelling is an important indicator of travel demand for subsidized developments, but this is largely a proxy for household size. Unfortunately, the number of residents per dwelling unit is not typically a piece of information collected in transportation impact studies, and neither are other potentially informative metrics or controls (e.g., household-level income, number of children or parents, or the age of the householder). Because of this, there is not currently enough information to do direct and nuanced comparisons of subsidized and market rate developments in this fashion. Do subsidized dwellings have similar household size rates (people per dwelling) compared with similarly sized market rate dwellings? Do people in San Francisco tend to live with more people per dwelling than those of Los Angeles or elsewhere? These are questions that standard transportation impact studies, including our own presented here, cannot typically answer. And without this information, it is problematic to translate findings from the market rate smart growth studies to this study on affordable housing. However, some emerging trends in development seem to be shifting towards more variation in dwelling schemes (e.g., micro-apartments, co-housing), and some agencies have started to encourage smaller dwellings (e.g., accessory dwelling unit) as policies to improve densities and housing affordability. In responding to these trends, it will become even more necessary to explore how changes in the structural characteristics of residential developments impact the configurations of households across developments, income-levels, and space.

While similar studies tend to focus on the land use impacts of motorized vehicle trip generation and use, this study explores the overall person trip activity generated at these sites. The findings indicate conventional estimation approaches may significantly underestimate person trip activity, and therefore non-motorized activity, at the site level. Currently, few studies explore overall multimodal activity (C. de Gruyter 2019), yet this is a key to understanding how to better estimate transit trips (for example) to and from each development. Methods that capture the synergistic or complementary relationships between mode choices and the environs of a site may allow for a greater understanding of the impacts of various multimodal transportation demand management strategies, such as adjustments of parking supply or inclusion of (un)bundled parking.

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