Predicting Travel Impacts of New Development in America's Major Cities
Testing Alternative Trip Generation Models

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There is a widespread belief that the available tools for predicting travel impacts of urban development are not as strong as they could be. The implications are that cities (*a*) may be hindered in developing appropriate travel impact mitigations, (*b*) lack good information to communicate to existing residents about potential travel impacts of proposed development, and (*c*) with better tools would be able to make stronger policy on the basis of more reliable understanding of development impacts. The most frequently used tool for estimating travel impacts is the ITE informational report on vehicle trip generation. The ITE report contains information primarily on single-use suburban automobile-oriented environments. As travel characteristics are inherently different in urban areas, a wide body of research has sought to create additional data-driven tools to estimate multimodal trip impacts of developments on the basis of urban-context characteristics. This paper compares the estimated trip generation outputs of the ITE and other models to field counts and surveys conducted for the District Department of Transportation at 16 locations in Washington, D.C. The findings here support the widely held belief that existing tools are not well suited to trip generation estimation in urban contexts. The paper is part of a larger study effort that seeks to develop a robust data set of urban trip generation that will be a foundation in the creation of better models.

The belief is widespread that the available tools for estimating travel impacts of urban development are not as strong as they could be. The implications are that cities (*a*) may be hindered in developing appropriate travel impact mitigations; (*b*) lack good information to communicate to existing residents about potential travel impacts of proposed development; and, (*c*) with better tools, would be able to make stronger policy on the basis of more reliable understanding of development impacts.

To address this concern, the District Department of Transportation (DOT) undertook a project to improve its understanding of urban, multimodal trip generation in Washington, D.C. The District DOT is interested in the question of how trip generation is shaped by the relationship between land use and transportation infrastructure in urbanized areas. The ultimate objective of the initiative is to develop

a better suite of tools to understand development impacts on urban transportation systems so that appropriate mitigations can be made. The project that is the source of this paper represents the intermediate step in developing a data collection methodology that captures multimodal trip-making behavior at the building level. The information will help the District DOT to improve the assessment of potential transportation impacts of new development throughout the District, ultimately providing guidance and the foundation for a national data collection effort to estimate multimodal trip generation in urban contexts. Part of the project included testing multiple trip generation tools against data that were collected at 16 exclusively residential buildings and residential buildings with ground floor retail establishments. These results represent the focus of the current paper.

Most cities rely on a variety of data sources, including ITE's trip generation rates, census data, and local ridership–travel behavior surveys to estimate impacts of new development on their transportation systems. Even when taken together, these sources fail to provide a robust idea of a development's transportation impacts. ITE's *Trip Generation Manual,* long relied on as the industry standard for predicting travel behavior, represents vehicle trip rates in areas with single-use, low-density zoning and land uses, frequently with limited or no pedestrian, bicycle, or transit infrastructure or amenities (*1*). Thus, with very rare exceptions, ITE rates are truly applicable only in contexts in which auto access is the dominant mode. ITE rates are given for automobile trips and, de facto, assume that most access and all impacts are because of automobiles.

Major cities, by contrast, are primarily dense and mixed use, and, in combination with the availability of walking, biking, and public transit modes, represent a very different trip-making context. This context is guaranteed to create fewer vehicle trips than ITE rates would predict and, quite possibly, more total trips overall (because of different trip-chaining patterns and greater density, for example). The limitations associated with ITE rates for this context are well understood, not least by ITE, which is currently embarked on a process to improve the applicability of its practice guidance for urban and mixed-use contexts. Census data also have limitations in that only journey-to-work trips are represented. The journey to work tends to have unique characteristics that are not necessarily representative of travel for other purposes; hence, inference to other trip types cannot be made from census data.

LITERATURE REVIEW

A comprehensive review of previous trip and parking generation studies was undertaken to inform this project. Attention was also focused on literature connecting trip making and mode choice with

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the built environment, even if the studies in question were not specifically about trip generation. Understanding built-environment effects on travel behavior will be critical for later model development, and built-environment characteristics figure prominently in six of the seven models described in this research. To be relevant, the work had to address place-based, rather than person- or household-based, trip generation. An obvious example of the former is described in ITE's *Trip Generation Manual* and of the latter, in any regional household travel survey. Person- and household-based trip generation, typically used for regional travel demand, relies on demographic factors for forecasting; when proposed developments are reviewed, demographics necessarily remain unknown; hence, any model must predict on the basis of physical characteristics of the proposed development.

A number of studies have focused on the impact of the built environment on trip generation and other travel behavior. The key indicators for travel behavior identified in this review are density, land use mix, parking price and availability, and the quality of nonautomobile modes. Researchers generally find correlations in consistent directions but different degrees for different variables. Travel behavior is measured as vehicle miles traveled (VMT) or vehicle hours traveled for private vehicles (*2–12*), mode share or propensity to use a given mode (*13–16*), or number of trips generated (*17–22*).

Density

Several researchers found correlations between residential and employment density, but not always both. For example, Zhang et al. found that residential density was correlated with a decrease in VMT in the four major metropolitan areas they studied but that employment density was statistically related to VMT in just two of the four (*2*). In a meta-analysis comparing the built environment and travel behavior, Ewing and Cervero found that household or population density had a negative correlation with VMT and a positive relationship with transit and walking trips (*12*). Ewing et al. found that activity density, represented by the sum of employment and population, was statistically significant in predicting the use of transit or walking but not in predicting internal capture rates or driving (*13*). Instead, the number of jobs within various multimodal radii of the site was a better predictor of driving.

Land Use Mix

Land use mix is usually measured as jobs–housing balance (*13*), as commercial-to-residential square footage (*23*), or by some kind of entropy measure that indexes land use diversity (*5, 13*). Studies generally find greater land use mix to be a predictor of lower VMT (*2, 5, 13, 23*) or of mode choice reflected as lower auto trips or more transit and walk trips (*2, 3, 12, 24*).

Parking Pricing and Availability

Several studies have looked at parking price and availability and concluded that parking pricing is a reasonable tool for managing travel demand–modal choice. Kelly and Clinch measured parking before and after a 50% increase in meter prices in Dublin, Ireland (*25*). They found that the price elasticity of demand of parking averaged −.28. A model based on field data from 240 multifamily properties in Seattle, Washington, found that, when parking price as a percentage of average rent increases, the number of vehicles per

occupied residential unit in multifamily residential developments decreases (*26*). Using household travel surveys, also in Seattle, Frank et al. found that per-trip parking charges had a negative influence on VMT, while transit price had a positive influence on VMT (*3*). Kuzmyak and Vaca found multiple examples for which parking pricing on its own or as part of a suite of transportation demand management strategies reduced trip rates, parked cars, or both (*15*). The study did not draw overall conclusions about parking pricing elasticity (*15*). However, research on parking cash-out at workplaces shows consistent reductions in the use of single-occupant vehicles (*15, 27, 28*).

In addition to price, the overall availability of parking can drive mode choice: driving is more burdensome when one is not assured a parking space. Lund et al. found that free parking at work had a negative impact on transit use (*29*), and Cervero (*30*) and Cervero and Arrington (*31*) found that, as the number of parking spaces per worker at offices increased, the number of transit trips decreased. The relationship is symmetrical: while greater parking availability is associated with more driving, decreasing available parking is also associated with less driving (*32*). In particular, Cervero et al. found that reducing parking by 0.5 space per unit can lower peak demand for parking by 0.11 parked car per unit in a suburban multifamily residential transit-oriented development (*32*). Looking at homes as well, Weinberger found that the availability of private parking at home was a predictor of private-automobile trips to the transit-rich Manhattan core of New York City (*33*). Conversely, or complementarily, lack of private parking at the origin was a predictor of higher transit.

Quality of Nonautomobile Modes

Transit quality is measured by frequency of service (*3, 17, 26, 31, 34*), presence of transit lines or stops (*14, 35, 36*), and stop–station density (*5, 13*). Invariably, researchers find correlations between these measures and transit ridership. Arguably, the presence of transit is a necessary, if insufficient, condition for transit usage.

Intersection density is the most frequently considered variable to predict walking, and it is a good proxy for block length as well [e.g., Ewing et al. (*13*), Chatman (*14*), and Clifton et al. (*37*)]. Some researchers find intersection density to be a good predictor of other modes (*13, 38*), reduced VMT, or both (*2*).

A measure similar to intersection density is the percentage of four-way intersections within a catchment area. Technically, this approach counts the percentage of intersections with four or more legs [i.e., a standard intersection (not a T- or staggered intersection)] at which two streets cross but also more complex intersections where more than two streets cross in a nonstandard grid. Cervero found the percentage of four-way intersections in an area was correlated with walk trips but not with trips by other modes (*30*). In contrast, Lund et al. found that this factor predicted transit choice (*29*). As noted earlier, Ewing et al. found that intersection density was a statistically significant predictor of transit trips, while the percentage of four-way intersections was a statistically significant predictor of walking and bicycling trips (*13*).

Bicycling Quality

In their survey of the literature, Heinen et al. found that researchers have evaluated the built environment and its impact on cycling trips in a myriad of ways, from the type of facility, to the number of vehicular lanes on a road, to the presence of stop signs and traffic

lights (*39*). One of the most common and relatively easy-to-measure variables was the presence of bicycle facilities. Carr and Dill found that the mileage of bicycle lanes in a city was correlated with census journey-to-work bicycle shares (*40*). The causality was unclear, but the presence of bicycle facilities may be robust as a heuristic to predict mode shares. Guo et al. found bikeway density to increase cycling for maintenance trips but did not find a corresponding drop in vehicle activity (*41*). Similarly, examining census data on commute mode shares before and after construction of cycling facilities, Barnes et al. found that areas near cycling facilities gained bicycle mode share when the facilities were built (*42*). The Oregon Transportation Research and Education Consortium model, developed by Clifton et al., considered the length of available bicycling facilities in predicting trips as well but ultimately found other factors to be better predictors (*37*). This pattern seems to be an overall trend: researchers either did not consider bicycle facilities or potentially considered other measurements such as intersection density to be sufficient to model bicycling opportunities and thus trip generation.

Redundancy, or collinearity, can exist among these variables; for example, although Clifton et al. considered transit quality variables, transit quality was ultimately dropped in favor of density measures, which they found to be more robust (*37*).

TOOLS FOR TRIP GENERATION ESTIMATION

Multiple tools that seek to provide trip–parking generation estimates for a variety of site types have been developed in recent years. Most efforts are in response to the concern that ITE trip generation rates are not well suited to urban in-fill, transit-oriented development, smart growth, and other high-density development types that are increasingly common. Despite the critique, most studies, like NCHRP Report 758 (*43*) and the California Smart-Growth Trip Rates Study (*17*), adjust ITE rates in an effort to better fit the different contexts. The tools, some of which are predicated on original-data collection, some based on secondary sources such as national- or municipal-data collection or household travel surveys, and others incorporating results from other studies (adapting their parameter estimates and findings to the task at hand), are summarized in Table 1 (*44–46*).

The problem of trip generation is not new, and neither is the concern that ITE may not be appropriate for predicting trip generation in all contexts (*47*). A 1985 report by FHWA, *Development and Application of Trip Generation Rates,* sought to complement the ITE methodology by incorporating rates based on location, auto occupancy, and transit availability (*48*). Other research, dating back almost 30 years, has offered alternatives while expressing the thinking that the standard approach is quite flawed and may need to be abandoned altogether (*49, 50*).

The primary conclusion of this review is that a good trip generation model should consider, at a minimum, measures of density, transit availability and quality, parking availability, and walkability. Other variables to consider are land use mix and the quality of bicycling infrastructure. The exact form that these variables should take will be determined by future research.

The secondary conclusion is that the ITE approach is not problematic prima facie but that relevant proxy sites for urban and in-fill development are lacking. Because of ITE's focus on suburban development over the past several decades, the organization has collected an impressive database from low-density settings. ITE reminds its users that "Data were primarily collected at suburban locations having little or no transit service, nearby pedestrian amenities, or travel demand management (TDM) programs" (*1,* Vol. 1, p. 1). As a result, urban sites are systematically underrepresented among the ITE data. The source of these data is not ITE itself; in fact, the *Trip Generation Manual* states that "ITE Headquarters conducted no original field surveys" (*1,* Vol. 1, p. 11). Rather, ITE describes its data sources as "contributed on a voluntary basis by various state and local governmental agencies, consulting firms, individual transportation professionals, universities and colleges, developers, associations and local sections, districts and student chapters of ITE" (*1,* Vol. 1, p. 11).

DATA AND METHODOLOGY

Collection Sites and Procedures

The study team collected data at 16 sites in the neighborhoods of Petworth, Columbia Heights, Navy Yard, and NoMa (north of Massachusetts Avenue) in Washington, D.C. Figure 1 shows the general location of these sites, labeled by neighborhood. A companion paper associated with the project outlines site selection and methodology (*51*).

Data were collected during winter 2013–2014. Data collectors counted and surveyed people entering and exiting the sampled buildings during peak morning and evening hours of 7 to 10 a.m. and 4 to 7 p.m., respectively. Surveyors intercepted subjects to learn and to record the most immediate or recently used mode before the subjects walked up to the interviewer (besides the act of walking from a parking space, bus stop, etc., to the front door.) Surveyors generally asked some variation of the question, "How did you get here today?" or "How are you getting to your next destination?" If the respondent drove, a follow-up question probing where they had parked was also asked. Also collected were site data, including the presence and use of bicycle racks, the quality of bus stops–shelters, proximity to Metro stations, and qualitative information about parking utilization and presence of publicly accessible parking lots.

Collection of Site- and Area-Specific Data

As discussed in the literature review, travel behavior, including number of trips and mode choice, is a function of land use and supply of transportation infrastructure. Given these established relationships, a robust trip generation model is reliant on site- and area-specific data. Hence, site- and area-specific data were collected to contextualize the trip counts appropriately. While much of the data are available in municipal or national databases and do not change over time, such as location of a rail transit station or a parking garage, other context variables, including parking utilization and quality of bus stops, may be time sensitive and not available from existing sources. This study did not focus on selecting context variables to build a model. However, the literature review identified several variables that would be good context measures. Therefore, to allow maximum flexibility in future development of trip generation models, the team also collected area-specific data to supplement those available from existing sources.

Site data were collected by using Google Earth, Zillow.com, the database of the Washington, D.C., Economic Development Partnership, and the database of the city's Real Property Taxpayer

TABLE 1 Trip Generation Estimation Tool Summary

Tool	Applicability	Data Set	Associated Publication	Input Summary	Output Summary
NCHRP Report 684 (2011)	Mixed-use developments (at least 3 uses).	Intercept surveys and door counts at 3 mixed-use developments in Florida and one each in Dallas, Tex., Atlanta, Ga., and Plano, Tex.	Boucher et al., 2011 (23)	Square footage of multiple uses. Proximity of uses (not required).	ITE-based vehicular trip reductions due to internal capture.
EPA-MXD Trip Generation for Mixed-Use Developments (2010)	Mixed-use developments.	Travel surveys from 239 mixed-use developments in U.S. urban regions.	Ewing et al., 2011 (13). SANDAG, 2010 (44). Fehr and Peers model overview (45). See citations for EPA-MXD.	Multiple context variables. Size of uses.	ITE-based vehicular trip reductions. ITE-derived transit trips. ITE-derived walking trips. Internally captured trips.
SANDAG MXD Trip Generation for Smart Growth (2010)	Adaptation of EPA-MXD model. Used for smart-growth developments in California.	Same tool as EPA-MXD, but with additional inputs from the *San Diego Traffic Generators Manual.*		Multiple context variables. Size of uses.	ITE–San Diego Traffic Generators vehicular trip rates.
California Smart-Growth Trip Generation Rates (SGTG) (2012)	Smart-growth developments (particular criteria given).	Door counts and intercept surveys at 30 smart-growth locations in California.	Handy et al., 2013 (17). Schneider et al., 2013 (46).	Multiple context variables. Size of uses.	ITE-based vehicular trip reductions.
URBEMIS 2007 software (2007)	All	Based on previous research.	na	Context and programmatic variables. Size of uses.	ITE-based vehicular trip reductions.
Portland State University (PSU) Models A, B and C[a]	All	195 travel surveys from Portland, Oregon; Puget Sound, Washington; and Baltimore, Maryland.	Currans and Clifton, 2015 (38).	Simple lookup table of activity density or multiple context variables.	ITE-based vehicular trip reductions (Adjustments A, B, and C) and trips by mode (Adjustment A only).
CAPCOA (2010)	All	Based on previous research.	na	Context and programmatic variables. Size of uses.	Quantification of pollution mitigation due to transportation measures; could be translated to trip reduction.
TRIMMS (2012)	All	Based on previous research.	na	Context, some demographic, and travel demand management programmatic variables.	Social benefits, including trip generation and reduction.
TripGenie (2012)	All	Based on previous site-specific counts.	na	Place type, and land use.	Trips by mode.
NCHRP Report 758 (2013)	Infill development (particular criteria given).	na—method recommendations rather than model.	na	Regional travel demand model data.	ITE-based vehicular trip reductions.

NOTE: na = not applicable; MXD = mixed-use development; SANDAG = San Diego Association of Governments; CAPCOA = California Air Pollution Control Officers Association; TRIMMS = Trip Reduction Impacts of Mobility Management Strategies.
[a]Model name created for purposes of this paper only.

Service Center. The consultant team collected site data at all data collection locations. The site data collection included the following key variables:

- Area (neighborhood),
- Name of project,
- Address,
- Major use (residential, commercial, or industrial),
- Total square footage,
- Office square footage,
- Number of residential units,
- Retail square footage,
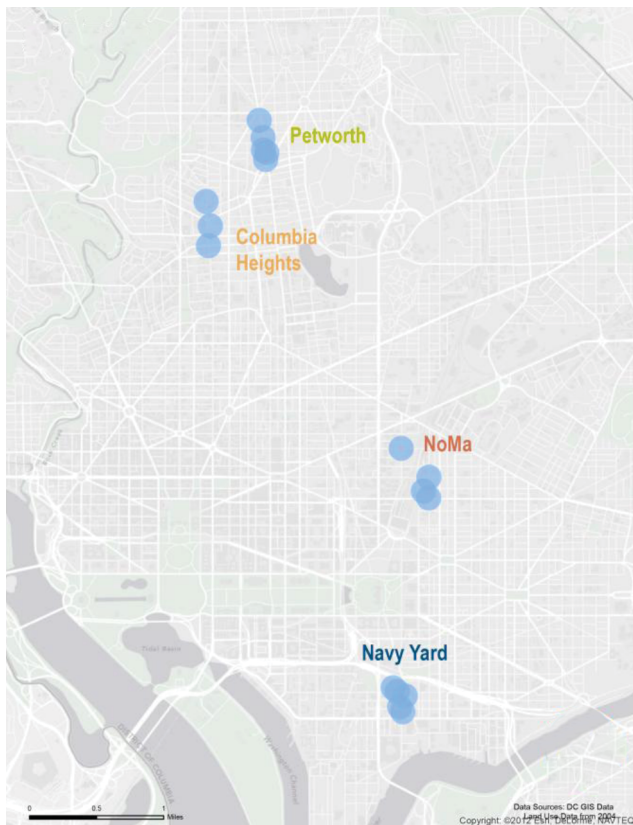- Parking space count, and
- Number of doors by type.

FIGURE 1   Site locations. (Copyright 2012 Esri, DeLorme, NAVTEQ.)

DATA COLLECTION RESULTS

Because the survey counted all persons entering and leaving the sites, trip generation is a simple count. Mode share, in contrast, was estimated from the sample of people surveyed. The ratio of counts to surveys was used as an expansion factor to derive an estimate of person trips by mode by door or funnel point. These data were then aggregated to form a total for each site. The expansion factors are specific to each count location and account for the fact that a door closer to a Metro station is likely to have a higher share reporting Metro as the main mode, while a door to a parking garage would have a higher share of vehicle trips. To address potential irregularities, mode shares, calculated over the entire 3-h period were applied to the peak hour to determine the mode splits.

While this section summarizes the data collected, the sample is small and, far from being a statistical sample, was deliberately stratified to encompass a variety of use and data collection contexts. Generalizations of the data with the goal of statistical inference are not warranted.

Perhaps not surprisingly, walking proved to be the dominant mode of travel, with a median value for the 16 sites of 40% and a maximum of 62%. As the box diagrams in Figure 2 show, private vehicle followed, with a median of 26% and maximum of 54%. Transit was also very close, with a maximum of 47% but a lower median, at only 16%. The very compressed lower end of the transit box plot indicates that transit usage at about half the sites was in a small range (in fact, between 11% and 16%), but the upper portion shows a much greater variation, with transit shares ranging from 21% to 47%.

Consistent with findings reported in the literature review, the research team found transit and drive shares to be substitutes (product–moment correlation coefficient −.6), while walk trips were complementary to both transit and driving. That is to say, the (negative) correlation between transit trips and private vehicle trips was greater than was the correlation between walking trips and private-vehicle trips. As transit trips increased, private-vehicle trips decreased sharply; as walk trips increased, private-vehicle trips decreased but not as precipitously. This finding suggests that transit and drive trips were substitutes while walk trips were complementary to both transit and driving.

As described in the next section, the preliminary conclusions that can be drawn from this effort serve truly to underscore the importance of the greater project contemplated. The high level of variability by seemingly similar sites indicates the idiosyncrasies of travel and the importance of developing a sufficiently large database that will allow for modeling of multiple contexts. For example, in the case of the Petworth-4 study site, the inordinately high number of auto trips results from the building's garage being open to the public; not all people parking there were accessing the building. Once a larger data collection is completed, correction factors can be added to account for these differences.

COMPARATIVE RESULTS

This section discusses seven approaches to estimating trip generation. The seven approaches were selected on the basis of accessibility, availability of documentation, and the context in which the model itself is applied. The predicted results of these models are compared with the trip generation counts and mode shares that estimated from field observations. The models are the following:

1. The ITE *Trip Generation Manual,* 8th edition (designated ITE) (*52*);
2. URBEMIS trip generation module (TGM) 2007, which is the most recent version of a tool developed for California air pollution control districts to calculate the expected air quality impact of development proposals (designated URBEMIS TGM);
3. The EPA mixed-use development (MXD) multiuse analysis method developed for the U.S. Environmental Protection Agency (designated EPA-MXD);
4. The California smart-growth trip generation model developed to estimate multimodal trip generation rates for proposed smart-growth land use development projects in California (designated SGTG); and
5. Three Clifton and Currans Portland State University models (designated PSU).

With the obvious exception of the ITE predictions, all the tools pivot from ITE trip generation. That is, the tools use ITE output as an input and adjust ITE trip generation that are based on a variety of identified trip reduction factors, such as density, mixed land uses, transit service, travel demand management programs, and other site characteristics. This entire section differentiates between estimated trips that are based on the District DOT's original data collection and predicted trips that are model outputs from the five individual or groups of models compared.

As expected the baseline industry standard, ITE trip generation systematically underpredicted person trips and overpredicted vehicle trips in the urban context.
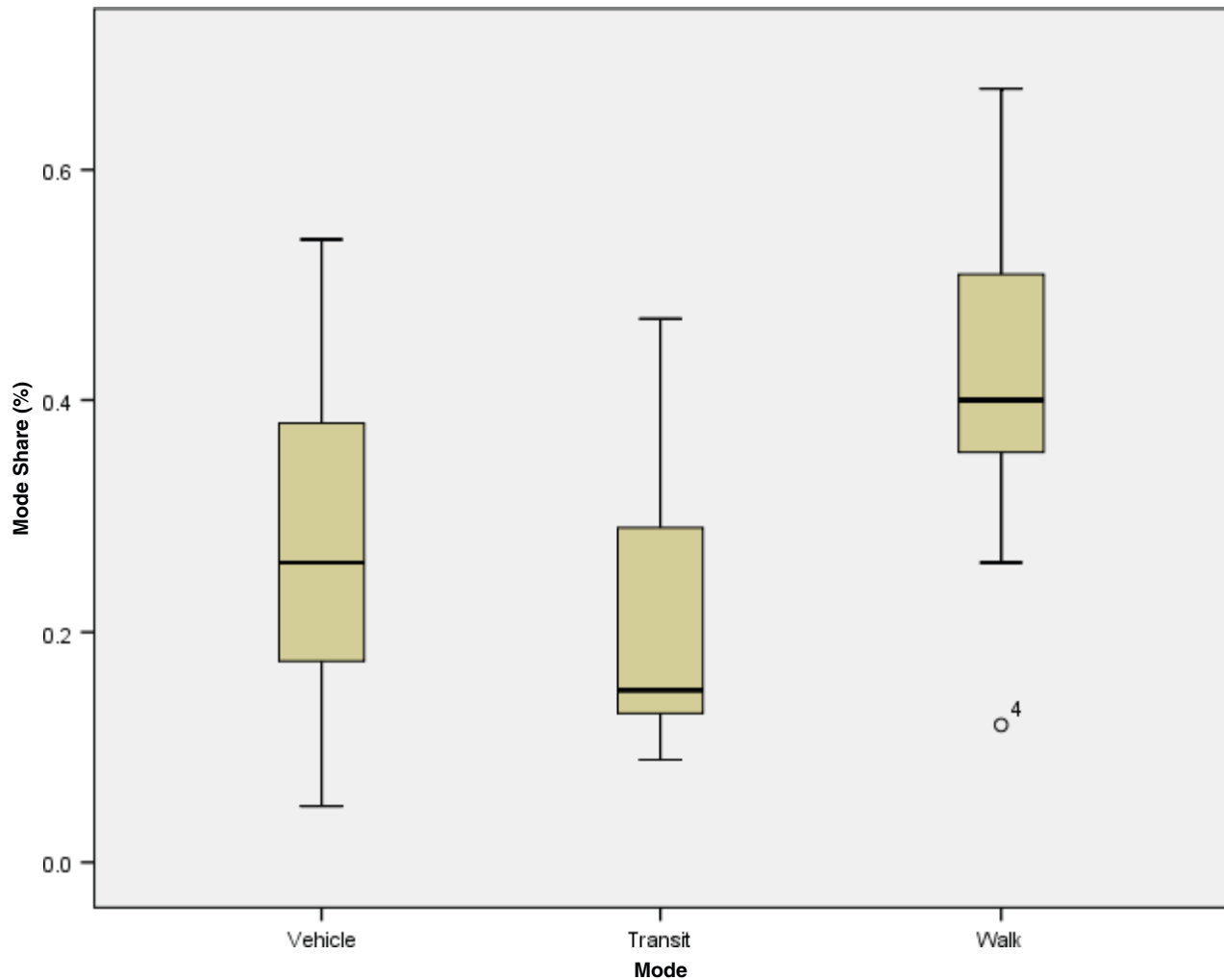
FIGURE 2   Variability in mode share: vehicle, transit, and walking.

ITE Data

Description

The ITE *Trip Generation Manual* is a compendium of vehicle counts taken at project sites across the United States (*52*). The compendium is unique as a crowd-sourced project that predates the Internet, but it is somewhat limited in that ITE had, for many years, stipulated an interest in single-use, low-density sites. Unfortunately, ITE rates are often applied in contexts where ITE explicitly suggests alternative approaches. The current results, presented below, corroborate the concern that development proposals for sites in dense urban areas, but assessed by using ITE rates, are penalized by being assumed to produce more vehicular trips than the environment can support. The projects are then frequently rejected or else overmitigated.

Results

Although ITE estimates vehicle trips, there is an assumption that vehicle and person trips are related. Given that data collection was done during peak periods, the authors assumed the journey-to-work average vehicle occupancy (1.13 persons per vehicle) as estimated in the National Household Travel Survey. On the basis of that assumption, ITE vehicle trip predictions underestimate person trips by about 15% in the morning and 27% in the afternoon (*53*). ITE vehicle trip predictions and estimated person trips compared with the data collected for this effort are illustrated in Figure 3, *a* and *b*.

Figure 4 shows the ratio of ITE-predicted private vehicle trips to observed private vehicle trips. The horizontal line on the graph lies at the value 1, which indicates a perfect, hypothetical correspondence between ITE predictions and field observations. Bars that exceed the line represent ratios greater than one, indicating that ITE overpredicted vehicle trips, while those below the bar, less than one, indicate that ITE underpredicted vehicle trips.

For most sites, ITE overpredicts the number of vehicle trips. Navy Yard-8 and Petworth-4 are exceptions. However, both buildings have garages that are accessible by members of the general public; thus, the high number of personal vehicle trips could result from the parking lot function rather than from residential use.

On average, ITE overpredicts vehicle trips at the pilot sites by more than 190% in both the morning and afternoon peak periods.
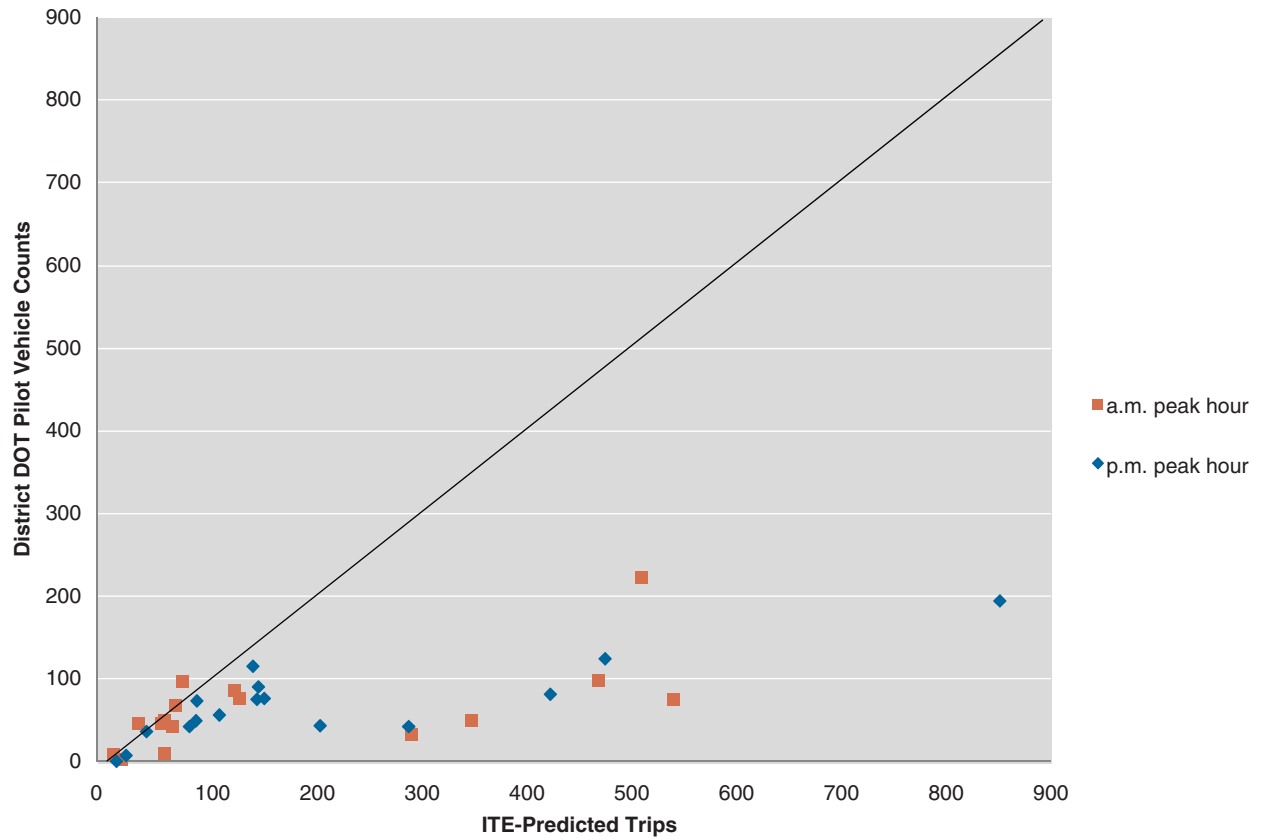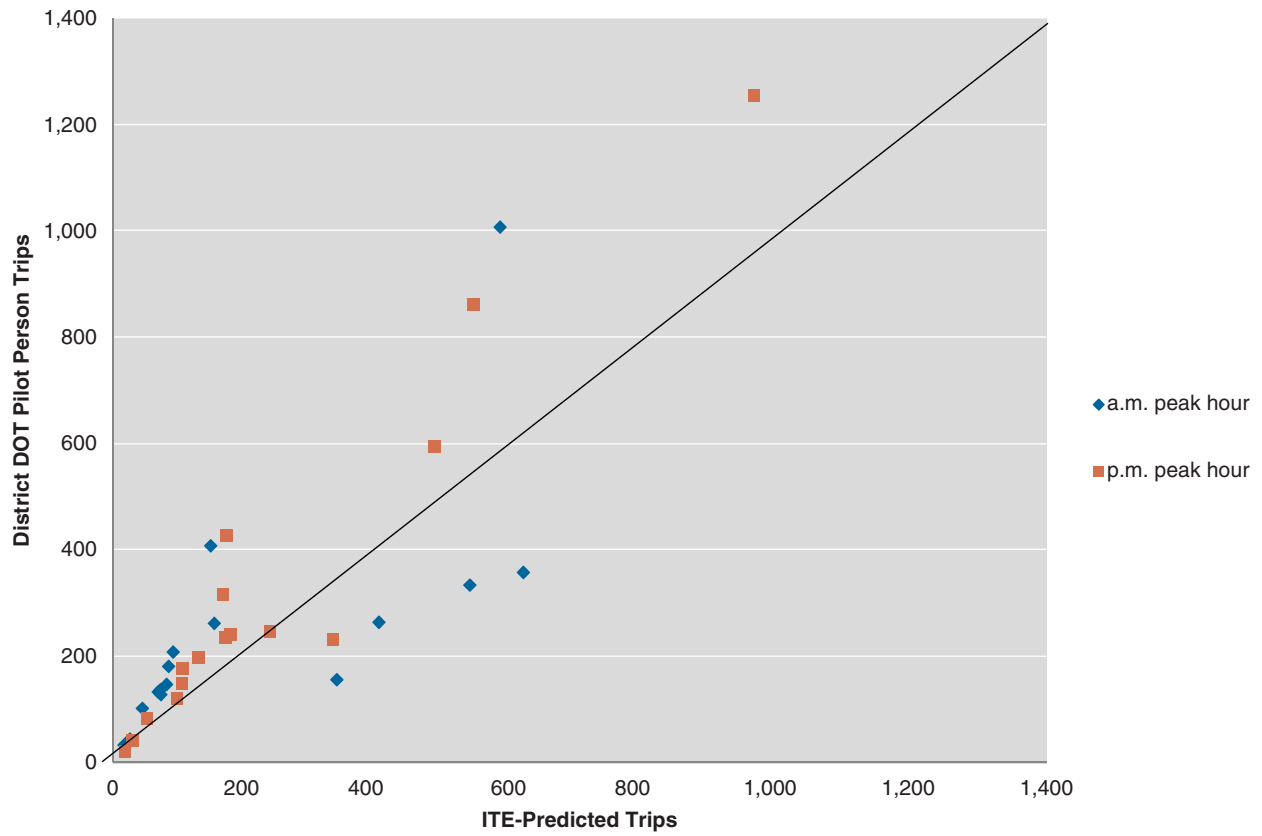
FIGURE 3 Graphs of (*a*) District DOT pilot vehicle counts versus ITE-predicted vehicle trips and (*b*) District DOT pilot person counts versus ITE-predicted person trips.
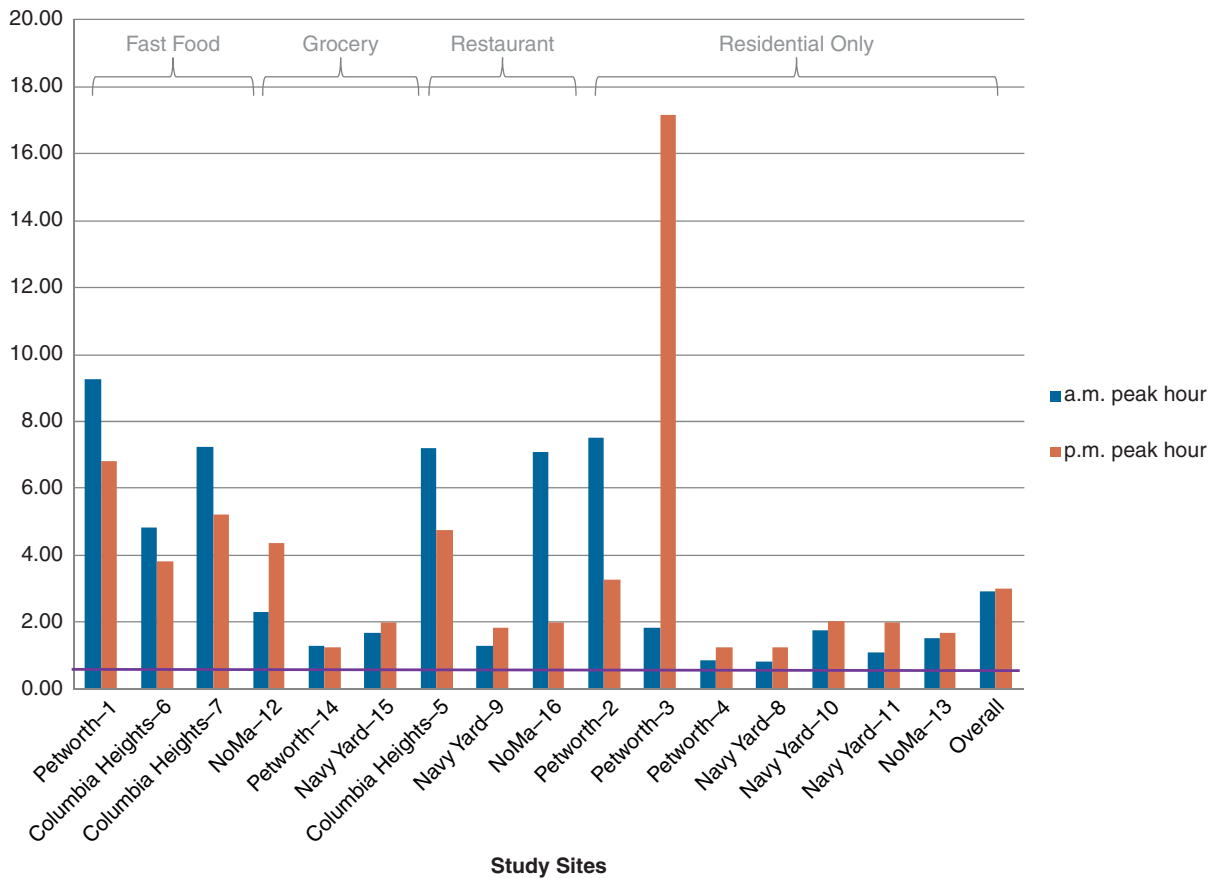
FIGURE 4 Ratio of ITE-predicted trips to District DOT estimated vehicle trips.

URBEMIS Data

Description

The California Air Resources Board developed the URBEMIS model to quantify and evaluate emissions from development projects in California. URBEMIS outputs are in the form of pollutant levels, which are a function of VMT.

Using an average trip length, the URBEMIS trip generation module converts estimated VMT to number of trips and applies trip reduction credits for urban context variables such as land use mix, pedestrian and bicycle facilities, and transit quality. The reductions given as a result of these factors are based on third-party research showing the effects of these variables on VMT, trip reduction, or both. Finally, the reduction credits are applied to ITE estimates to develop a trip generation estimate that considers the development context.

The URBEMIS 2007 version, which is the currently disseminated software, uses ITE trip rates from the 7th edition of the *Trip Generation Manual* to calculate the baseline raw trips (*54*). Data needs for URBEMIS are relatively high; however, sources for these data are easily found from census, Google Earth, and publicly available GIS data such as census Topologically Integrated Geographic Encoding and Referencing (TIGER) data or statewide databases.

As URBEMIS does not provide diurnal output, peak hour results shown here are derived by applying ITE peak hour percentages to the URBEMIS daily output. The results are minimally inconsistent, as URBEMIS outputs are based on ITE's 7th edition (*54*) while the

peak hour factors are from the 8th edition of the *Trip Generation Manual* (*52*).

Results

On average, URBEMIS predictions are closer than ITE predictions to field results, with overprediction of vehicle trips closer to 117% in the morning peak and slightly higher, at 136%, for the afternoon peak.

EPA-MXD Data

Description

The EPA-MXD model is based on research published in Ewing and Cervero (*12*). It is estimated on the basis of observations from 239 mixed-use (or multiuse) developments in the urban areas of Atlanta, Georgia; Boston, Massachusetts; Houston, Texas; Portland, Oregon; Sacramento, California; and Seattle, Washington. The tool has been adopted, and in some cases adapted, by multiple regions in California, Washington, New Mexico, and Virginia.

The EPA-MXD spreadsheet tool uses context variables such as intersection density and jobs–population balance to calculate vehicle, transit, and walking trips on the basis of ITE estimates. However, the ITE estimates used in the model are slightly different from

those calculated earlier in this study, as the model limits the number that can be used as inputs. For example, ITE Code 222, high-rise apartment, which was used to develop the ITE predictions, is not an option: the user instead must select from high-rise condominium (Code 232) or multifamily (Code 220).

Results

Although the authors apply the model to the District DOT data, the EPA-MXD is actually poorly suited to the current context. First, the model is designed to estimate trips across a minimum 5-acre site to account for all development in the catchment area, including the proposed development for which travel impacts are being considered. If one assumes that a city block is about 300 ft long, this area is about two and a half city blocks. The proposed method for single-site analysis is to apply the model at a suitable geography with, and then without, the proposed development. The difference in those results should yield the expected impact because of the development. Unfortunately, the detailed land use data necessary to do so were unavailable for this project.

Results are therefore provisional and differ from the correct results by an internal capture factor. Larger (150+ units) and purely residential buildings performed well in the model compared with smaller ones (49 to 75 units). Somewhat surprisingly for a model that is meant to be robust to internal capture, for sites with multiple uses, the model generally overpredicted vehicle trips by factors of 91% and 122% in the morning and afternoon peak periods.

SGTG Data

Description

SGTG is a methodology and spreadsheet tool that estimates vehicle, transit, and walking trip generation rates at smart-growth developments. The SGTG project team, based at the University of California, Davis, collected trip generation data at 30 smart-growth sites in California. Comparing their field data with ITE trip generation rates and stratifying by various context variables, the team created a model to adjust ITE trip generation rates on the basis of the context variables considered. The model relies on a blended smart-growth variable that derives from eight site-level and context factors. These factors include population, jobs, distance to central business district, average building setback, presence of metered parking, transit service frequency, and percentage of the site devoted to parking. Trip generation is then estimated by using a linear regression model of the following form:

$$\text{adjustment factor} = a + b_1 * \text{SMG} + b_{2i} * \text{landuse}_i$$

where

  a and b_j = estimated parameters,
    SMG = smart-growth composite variable, and
  landuse_i = vector of 0–1 variables indicating membership in land use class i indexes.

The model spreadsheet tool applies the calculated adjustment factor directly to ITE-predicted trips.

The model report notes that in addition to using the SGTG model to determine whether a site is suitable for this analysis, the model is also only applicable for single-use sites or single land uses that are

part of multiuse sites. For the 16 sites in the District of Columbia region, six of the single-use sites did not meet the smart-growth criteria, and all mixed-use sites technically did not either; thus only three sites were actually consistent with the SGTG requirements. The model documentation warns that, for sites that do not meet criteria, the SGTG may overestimate the ITE rate adjustment. As the next section discusses, that warning seems to be borne out.

Results

Although the results vary widely, the overall number of vehicle trips predicted is similar to what was observed. Generally, vehicle trip rates were slightly higher in the morning than the model predicted, while the afternoon trips were lower than the SGTG results. The use does not appear to play a role in how closely the results matched here. In addition, the sites that did not meet the smart-growth criteria would be expected to have ratios higher than one, but that is true only for about half the observations.

A look only at sites that fit the SGTG model criteria (Navy Yard-10, Navy Yard-11, and NoMa-13) shows that the model consistently underpredicted vehicle trips in the District DOT context. Although the model underpredicted morning trips by 62%, it was much closer for the evening, underpredicting by just 22%.

Data on PSU Models

Currans and Clifton developed a suite of three models that were based on travel surveys from Oregon, Washington State, and Baltimore, Maryland (*38*): Adjustments A, B, and C. Using the National Household Travel Survey, the PSU models first convert ITE vehicle trips to person trips; then a second process divides the person trips into modal shares to yield a new set of vehicle trips and transportation impact estimates.

The person trip calculations are based on general land use category and trip characteristics such as time of day. The authors concluded that activity density was a simple and appropriate proxy variable for the urban environment for each general land use category. However, they noted that the performance level of this model was not high and that vehicle occupancy was likely more strongly correlated with another variable not included in their analysis. These occupancy rates were applied to ITE estimates to calculate ITE person trips to each site.

Adjustment A estimates trips by mode on the basis of mode shares developed for different urban density ranges. Calculating trips by mode is as simple as calculating density within a half-mile buffer of the site and then using a lookup table to estimate mode share. That mode share is then applied to a person trip number modeled from ITE-predicted vehicle trips.

Adjustments B and C are models that give the odds that an individual will travel by car for a given trip. Adjustment B is based on intersection density, while Adjustment C examines other land use variables such as distance from the central business district and whether the site is near a transit-oriented development. Rather than adjusting ITE directly, the adjustments are applied to the person trips derived from applying the vehicle occupancy models to ITE rates.

The advantages to these models are that their data requirements are relatively few and that the data required are fairly accessible.

Overall, Adjustment A of the three models gave the closest results for vehicle trips despite being the least complex. Adjustment A

overpredicted vehicle trips but by the small margin of 11% and 8% for the morning and evening peak hours, respectively. The PSU Adjustment B model underpredicted vehicle trips for many sites, underpredicting overall by 60% of trips in the morning peak and 51% in the evening peak. Adjustment C provided a closer fit, but it underestimated vehicle trips by about 59% in the evening and 32% in the morning peak hours.

Summary

Figure 5 shows overall results for the seven models. Data are presented as the ratio of predicted vehicle trips from each model to the vehicle trips estimated from the field work.

The overall finding that ITE underpredicts urban trips is consistent with the team's expectation. The finding that ITE overpredicts vehicle trips is also consistent. The models currently available predict slightly better than ITE but all do so by applying reductions to baseline ITE predictions. Because no theoretically compelling argument suggests that single-use suburban data would systematically translate to multiuse urban contexts, the finding underscores the importance of developing better tools to predict vehicle trips as well as trips by other modes. Furthermore, to plan trip impacts in urban environments adequately, trip generation must go beyond auto trips to include impacts on a broad set of travel modes.

CONCLUSION

The study was undertaken to confirm, and to begin addressing, a gap in tools available to the District DOT (and other transportation agencies in urban locations) related to estimating the transportation impacts of new developments. Many jurisdictions rely heavily on ITE's database of trip generation studies to derive trip generation predictions. Despite their limited applicability to single-use and sub-urban contexts, the ITE data frequently form the foundation of travel impact analyses in multiuse and urban contexts. The District DOT is committed to developing more-precise estimates of travel impacts to make better policy decisions with respect to required mitigations.

As a first step, the District DOT developed this project to create a data collection methodology that could ultimately lead to a national system of data collection and tools that are applicable in urban contexts for better prediction of trip generation and travel impacts. The project also required a pilot data collection effort to ground-truth the methodology (51). As a final component, the project tested existing tools to assess their ability to predict the data collected.

The study confirmed that most existing models systematically overpredict automobile impacts and may underpredict person trips. Further data collection is needed to verify the preliminary results of this study and to develop a new suite of tools. In the immediate term, results of this study are likely to alter the District DOT's approach to several areas of planning practice. Armed with a more accurate assessment of a proposed project's impacts, the District DOT can more
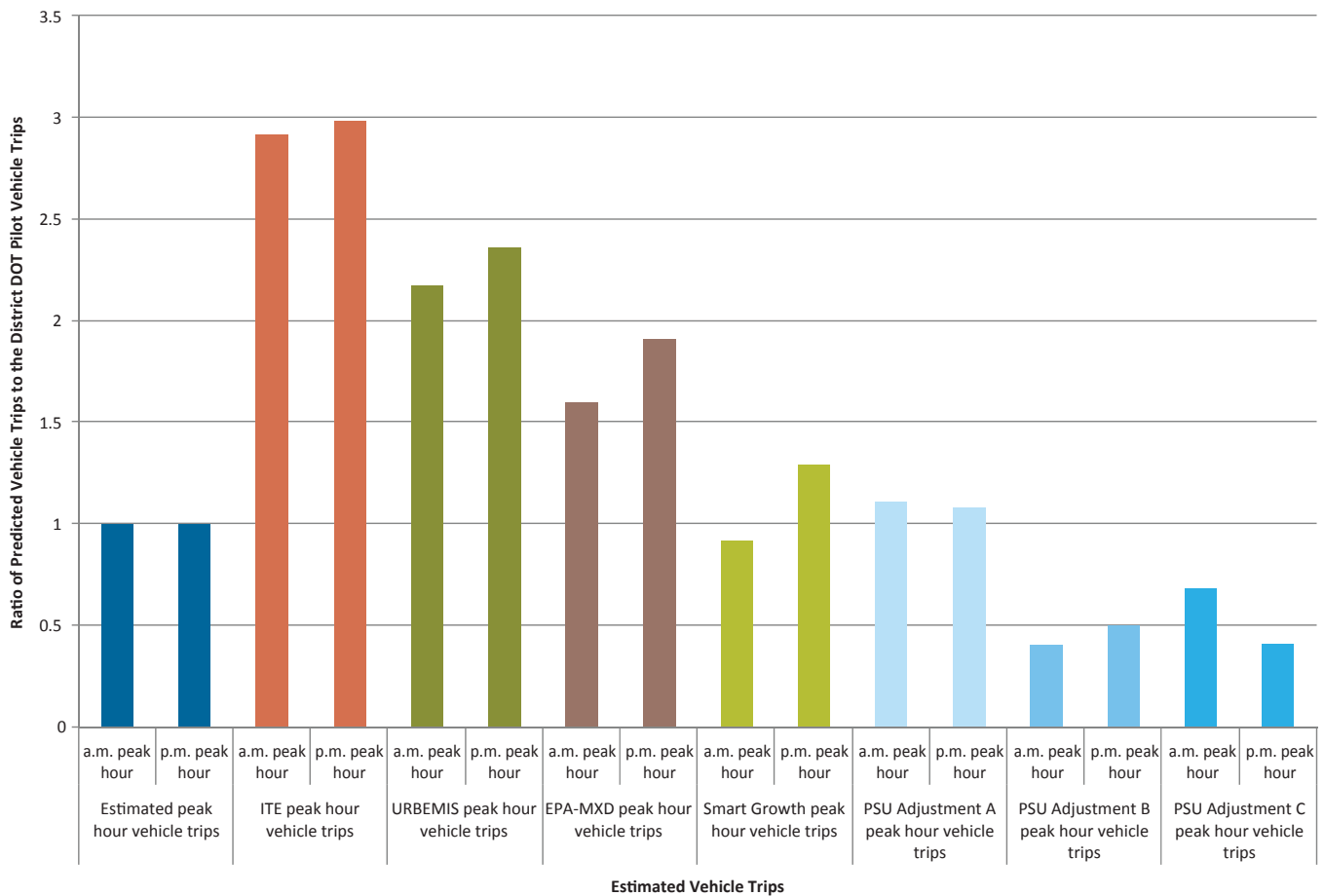

FIGURE 5   Ratio of model results to the District DOT estimated vehicle trips.

effectively diagnose likely transportation problems and garner more appropriate mitigations at the site level. This improvement, in turn, will help to develop the District's multimodal transportation system further. In addition, a fuller understanding of a development's impacts can also assist in addressing of traffic impact concerns from residents, decision makers, and other stakeholders. Finally, the research could lead to better Districtwide policy making by basing mitigations and policies about mitigations on how residents are actually making trips.

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