Households with constrained off-street parking drive fewer miles

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Abstract
Parking supply is one of the most neglected elements of the built environment in travel behavior research, despite evidence linking parking with vehicle use. As transportation impacts of new development are increasingly measured by vehicle miles traveled (VMT), explicitly connecting parking characteristics with vehicle travel is necessary to better inform transportation and land use policy. In this paper, we begin to address this research gap and explore the relationship between constrained parking and household VMT. Utilizing the 2017 National Household Travel Survey (NHTS) California add-on sample, we estimate residential parking constraint for households in Los Angeles County. Then, we develop a two-level model framework. Level 1 (Cost) models estimate travel costs, represented by vehicle ownership as a function of parking constraints, the built environment, and demographics. Level 2 (Demand) models regress household-level total and home-based-work VMT on predicted vehicle ownership, controlling for temporal and environmental characteristics. To further explore the relationship between parking and VMT by place type, we applied Level 1 and Level 2 models to develop a suite of scenarios for typical households in Los Angeles County. Our findings support the hypothesis that the built environment (including parking) influences VMT through travel costs (vehicle ownership). Results from scenarios analysis reveal constrained on-site residential parking (< 1 parking space per dwelling unit), accounts for an approximate 10–23 percentage-point decrease in VMT within each place type. Finally, implications for practice and future research are presented.

Keywords Parking · VMT · Development-level · Transportation impact analyses · Vehicle ownership

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Introduction

Parking supply is one of the most neglected elements of the built environment in travel behavior analyses. Despite ample research acknowledging and exploring the importance that parking—or specifically unconstrained and free parking—plays in dominating the urban landscape, only a few studies have statistically linked higher rates of parking supply with greater levels of vehicle use (Chatman 2013; Shoup 2017; Guo 2013; Appleyard 2012; Ewing and Cervero 2001; McCahill et al. 2016; Van Acker and Witlox 2010; Millard-Ball et al. 2021). This gap stems from the dearth of parking-related data, which makes it difficult to explore the influences of parking on vehicle demand (Currans et al. 2020a; Manville 2017). Although it is widely recognized in practice that parking regulations play an important role in managing vehicle demand (Shoup 1997), there is no practice-ready framework for incorporating parking into the development review process, even as impact assessment shifts from level of service (LOS) to vehicle miles traveled (VMT)-based metrics (Governor’s Office of Planning and Research 2016). Transportation impact studies, for example, have conventionally ignored the influence of parking supply on vehicle demand (Currans et al. 2020b). In this study, we explore the influence of off-street parking supply on VMT to inform the extent to which parking policies (pricing, supply, etc.) can be incorporated as policy-levers to reduce vehicle demand into alternative modes or to develop policies that are more effective in meeting planning goals and objectives.

In recent years, public agencies have moved to align development-specific transportation impact evaluations with regional goals. Washington, D.C., for example, has adjusted their parking guidelines to accommodate the relationship between vehicle demand and impacts and off-street parking.\(^1\) In California state legislation requires new development to be evaluated in terms of vehicle miles traveled (VMT) thresholds linked to greenhouse gas reduction goals and targets.\(^2\) One strategy identified for lowering VMT considers parking reduction and pricing policies (Boarnet and Handy 2017). While there is clear evidence that unconstrained (free and readily available) parking supply influences vehicle demand, few studies are designed in a way that provides the nexus to quantitatively justify altering parking guidelines in response to mode share or vehicle demand goals and performance metrics.

In response to these gaps in research, we ask: how does residential, off-street parking supply influence household VMT? In this manuscript, we first explain our analytical framework in the background section, which explores the complex influences of parking, the built environment, and demographics on vehicle use (Currans et al. 2020a). With Los Angeles County as our study area, we focus on the influence of constrained on-site residential parking (e.g., developments with less than one parking space per dwelling unit on average) on vehicle use (VMT). Following, we discuss our methods and data, organizing our analysis through a practitioner-oriented lens. One of our guiding principles for this research is to link these findings to practice. As such, we have taken care to select a methodological path that may be intuitive to practitioners and decision-makers, as well as academically rigorous. Consequently, in the results section, we present the findings from our regression analysis and then apply these results through scenarios that depict relative differences of vehicle use across contexts (urban place types and parking constraints). While the findings

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1 See [https://planning.dc.gov/page/parking-utilization-study](https://planning.dc.gov/page/parking-utilization-study).
2 See [https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201320140SB743](https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201320140SB743).
from the regression analysis indicate significance and effect size, the translation of the findings into scenarios provides guidance on how the relative impacts of off-street residential parking may influence development-level VMT demand across urban forms.

**Background**

The literature is clear: parking matters when considering vehicle demand. Research by McCahill et al. (2016), which drew on existing research and original data from nine U.S. cities over forty years, suggested that incremental parking increases have contributed substantially to rising automobile use in cities. Notably, an increase in citywide parking from 0.1 to 0.5 spaces per resident or employee was connected to a difference in automobile mode share of 30 percentage points for commute trips. In one of the few studies to connect parking to vehicle use at the development-level, Currans et al. (2020b) found residential sites with higher off-street parking ratios to be one of the strongest significant predictors of vehicle trip rates at subsidized affordable housing developments. And in the context of transit-oriented development (TOD), Chatman (2013) found scarce off-street parking significantly reduced the probability of commuting by single-occupied vehicle (SOV) after controlling for housing age, distance to rail, demographics, and preferences. Bundling residential parking with rents has also been linked to increased rates of vehicle ownership and probability of commuting by car (Manville 2017). More recently, Millard-Ball et al. (2021) conducted a survey of households who participated in a residential lottery and found that parking availability did influence vehicle use without limiting job mobility. Because of the inherently random nature of the residential lottery, this study provides evidence that parking supply does influence vehicle use.

Despite some strong theoretical reasoning and empirical evidence on the importance of parking, few studies exploring the relationship between the built environment and travel behavior have incorporated parking explicitly (Stevens 2017). As a result of this gap in research, the mechanism through which parking influences vehicle use, and VMT specifically, is unclear. Currans et al. (2020b) synthesized the thinking of two commonly cited areas of work—van Acker and Witlox (2010) and Crane, Boarnet, and Crepeau (CBC) (Boarnet 2011, p. 20; Crane and Boarnet 2001; Crane and Crepeau 1998)—developing a
conceptual map linking residential parking characteristics with vehicle use (see Fig. 1). While neither van Acker and Witlox nor CBC consider parking explicitly, Currans et al. (2020a, b) extrapolate the authors’ considerations of the built environment to include parking policies.

In CBC’s collective work, the authors asserted that built environment characteristics influence vehicle use through travel prices, measured by average travel distances and speed observed for each household (Boarnet 2011, p. 20; Crane and Boarnet 2001). For example, in San Diego, California, Crane and Boarnet (2001) show that travel costs, proxied by travel distances and speeds, were significant predictors of non-work vehicle trips, even when controlling for built environment characteristics. To explore this further, the authors estimated a two-step model, first estimating travel distances and speeds, and then non-work vehicle trips using those predicted values. They find that land use variables were significant predictors of travel speed, and subsequently, predicted values for travel speed significantly predict vehicle trips.

In van Acker and Witlox (2010), the authors tested the hypothesis that car ownership—a fixed, long-term cost of travel—mediated the impact of the built environment on vehicle use. The authors utilized structural equation modeling (SEM), which allowed for differentiation between the direct and indirect effects of each predictor on vehicle use. Of five built environment characteristics tested (built up index, land use diversity, distance to railway station, distance to CBD, accessibility by car), all measures exhibited direct effects on vehicle ownership, but only one (built up index) was found to have a direct effect on vehicle use. The remaining measures only affected vehicle use indirectly through vehicle ownership. Demographic information, including age, marital status, and employment, had both direct and indirect effects on vehicle use, where the indirect effects were also similarly mediated by car ownership. Household income produced a direct effect on car ownership, and an indirect influence vehicle use.

Based on these two theoretical approaches, we emphasize in our framework that the built environment—including parking supply—is expected to influence vehicle use through fixed and variable travel costs, like car ownership and commute distances. In the next section, we describe how we apply this framework for associating residential, off-street parking with VMT. In this paper, we rely on the framework in Fig. 1 as the basis for a series of models for estimating residential VMT (Currans et al. 2020a). Our model framework is described in detail in the next section. In addition to summarizing model results, we provide a series of post-hoc analyses that validate some of the relationships explored and demonstrate how our models could provide a useful basis for practice, enhancing the body of research supporting the link between vehicle demand and development-level parking.

**Methods**

This section explains the method used to apply this framework shown in Fig. 1, and the following section describes the data representing each variable. To operationalize this work, we adopt a two-step method similar to CBC’s, but one that incorporates the effects of parking supply (Fig. 2). In the Level 1 (Cost) models, we explore the influence of the built environment as represented by place type, demographics (household size and income), development type (single-family and multifamily), and parking supply on vehicle ownership, a key fixed household “cost” related to travel as identified in
previous literature. For example, the importance of direct influence of demographics on vehicle ownership was a key finding from van Acker and Witlox (2010). A negative binomial model was used to estimate vehicle ownership.

In Level 2 (Demand), total and home-based-work VMT were regressed on predicted vehicle ownership with additional controls for zero-worker and telecommuter households, travel day and month, and accessibility (transit to auto job access, percent retail employment). Of the full sample used to build the total VMT model, 12% of households made no vehicle travel on their survey day. In the subset of households used for weekday home-based-work VMT estimation, almost half (45%) made no home-based-work VMT. To account for the truncation and clustering around zero of these outcome variables, a Tobit model specification was used to estimate total VMT and home-based-work VMT (Shin 2020).

While van Acker’s structural equation modeling approach allowed for the testing of direct and indirect effects by simultaneously estimating relationships, we apply our framework through the CBC lens so that the results are easier to apply in practice. Therefore, we must be cognizant about incorporating the same or highly correlated variables that might inflate the significance of within Level 2 regressions. Throughout the iterative model development, variance inflation factors (VIF) were used to identify issues with multicollinearity through our two-step process. To decide the appropriate level to incorporate each variable, we recognize the findings from van Acker that suggest the strongest influences of the built environment and demographics are mediated through vehicle ownership. However, we test for VIF as a means for exploring whether the strength of a Level 1 variable creates multicollinearity issues through predictive variables in Level 2. Some measures of the built environment not highly correlated with regional location—such as percent retail employment—can be introduced into the Level 2 estimates of demand without biasing the model.
Post-hoc analysis: testing for the mediating effects of vehicle ownership

To evaluate the claim that the impact of parking on vehicle travel is mediated by vehicle ownership, we consider the relationship between three variables, $X$, $Y$, and $M$, in Fig. 3 (adapted from Preacher and Hayes (2004)):

As described by Baron and Kenny, “a given variable may be said to function as a mediator to the extent that it accounts for the relation between the predictor and the criterion” (Baron and Kenny 1986). The top portion of Fig. 3 expresses a simple regression of $Y$ on $X$, where the effect of $X$ on $Y$ is $c$. In the bottom portion of the figure, a mediator, $M$, is entered into the relationship. Now, there is a direct effect of $X$ on $Y$ ($c'$), as well as an indirect effect of $X$ on $Y$ mediated through $M$ ($ab$). Mediation thus describes the process or mechanism through which $X$ might affect $Y$.

While mediation analysis is widely utilized in psychology research, it has been used increasingly in the transportation field (van Acker and Witlox 2010; Mishra et al. 2015; Nguyen et al. 2017; Kamel et al. 2019). The framework proposed by Fig. 2 suggests that the impacts of the built environment, including parking, are mediated by travel costs, namely vehicle ownership. As previously discussed, our framework builds on the approaches of CBC (Boarnet 2011, p. 20; Crane and Boarnet 2001) and van Acker and Witlox (2010), who both suggest or test for similar mediation effects. While van Acker and Witlox (2010) employ structural equation modeling (SEM) to examine direct and indirect effects, we opted for the two-step framework outlined in Fig. 2 for ease of use in practice. Thus, we rely on other established approaches for testing mediation.

We examine mediation effects from two analytical standpoints. First, we adopt a post-hoc, exploratory approach using the Baron and Kenny (1986) approach for causal mediation.3 Baron and Kenny (1986) propose a four step process to establish causal mediation, given an independent variable $X$, dependent variable $Y$, and mediator $M$. The authors assert that mediation occurs if:

1. $X$ is a significant predictor of $M$
2. $X$ is a significant predictor of $Y$4

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3 Note that the use of this particular test is being conducted in an exploratory manner to compare results to the other mediation approach and potential mediation effects generally. Our model framework is not set up to establish causality, nor is the purpose of this analysis to establish causality.

4 As noted in Preacher and Hayes (2008), there is support that mediation can still occur if Step 2 does not hold true, such that mediation effect is determined by Steps 1 and 3.
3. M is a significant predictor of Y controlling for X
4. The effect of X on Y is less in Step 3 than in Step 2

Despite its prevalence of use, the Baron and Kenny approach has been criticized for lacking statistical power, potentially resulting in excessive Type II error as a result (Preacher and Hayes 2004). Because of this, we also consider a second approach in calculating the indirect effect of parking on VMT (via vehicle ownership) and testing it for significance. We employ a bootstrap approach to the above four-step process, as described by Preacher and Hayes (2004), given its (a) flexibility to handle a wide variety of distributions of data and (b) non-reliance on large sample sizes to demonstrate significant effects. We utilize the mediation package in R to carry out the 5000 re-samples needed for this analysis.5

As noted in Preacher and Hayes (2008), there is support that mediation can still occur if Step 2 does not hold true. In other words, the mediation effect is primarily dependent on Steps 1 and 3. Therefore, while we present results for Step 2, we focus on Steps 1 and 3 for evaluating the existence of a mediation effect.

Data

In this section, we describe the primary and secondary data collected for this study. Descriptive statistics for our sample data are included in Table 1.

National household travel survey California add-on sample (2017)

The National Household Travel Survey captures daily trip-making profiles in the U.S. (USDOT FHWA 2017). Undertaken roughly once every seven years, the survey compiles 1-day travel diaries from a sample of individuals and households, collecting information about trip purpose, mode choice, and travel time. In the 2017 survey, the California Department of Transportation (Caltrans) purchased an add-on sample of California-based households, which we use for this analysis. For each household, we received permission to access geocoded household information, allowing incorporation of additional built environment information with this sample (see the following sub-sections).

The residential vehicle impacts are typically evaluated at the development-level in practice, often by “dwelling units.” Therefore, we organize the data into a household unit-of-analysis, a proxy for dwelling units. We restrict our sample on Los Angeles County. For each household, we summarize the total and homebased-work VMT which include only personally driven trips made by car, SUV, pickup truck, van, motorcycle/moped, RV, or rental car. This ensures trips with multiple household members are not double counted in household VMT. Additionally, this definition excludes personal carpool, taxi, or transportation network companies (TNC) pick-up or drop-off situations where households’ residential parking may not be utilized on either end of the trip. Homebased-work VMT is defined as the subset of total VMT where the trip origin or destination was at home and the trip purpose are traveling to or from work.

5 Tingley et al. (2013) mediation: R Package for Causal Mediation Analysis. R package version 4.4.2, URL http://CRAN.R-project.org/package=mediation.
Table 1 Descriptive statistics of dataset

| Variable                                      | Scale | N  | Min | Max  | Mean  | SD   |
|-----------------------------------------------|-------|----|-----|------|-------|------|
| Household size                               | HH    | 2072 | 1   | 9    | 2.22  | 1.25 |
| Household size squared                       | HH    | 2072 | 1   | 81   | 6.50  | 7.94 |
| Number of workers                            | HH    | 2072 | 0   | 7    | 1.20  | 0.90 |
| Household income                             | HH    | 2014 | 5000| 300,000 | 100,752 | 84,167 |
| Vehicle ownership                            | HH    | 2072 | 0   | 9    | 1.88  | 1.13 |
| Total VMT                                     | HH    | 2072 | 0   | 616  | 40.80 | 53.70 |
| Homebased-work VMT                           | HH    | 2072 | 0   | 190  | 11.81 | 22.71 |
| Zero-worker household flag                   | HH    | 2072 |     |      |       |      |
| Household has workers                        |       |     |     |      |       |      |
| Zero-worker household                        |       |     |     |      |       |      |
| Telecommuter household flag                  | HH    | 2072 |     |      |       |      |
| Non-telecommuter household                   |       |     |     |      |       |      |
| All household members telecommute            |       |     |     |      |       |      |
| Survey day                                   | HH    | 2072 |     |      |       |      |
| M–Th                                         |       |     |     |      |       |      |
| Fri                                          |       |     |     |      |       |      |
| Sat/Sun                                      |       |     |     |      |       |      |
| Survey month                                 | HH    | 2072 |     |      |       |      |
| Summer months (June, July, Aug)              |       |     |     |      |       |      |
| Winter months (Nov, Dec)                     |       |     |     |      |       |      |
| Other months                                 |       |     |     |      |       |      |
| Parking ratio (PR)<sup>b</sup>               | D     | 2059 | 0   | 5    | 1.82  | 0.83 |
| Parking constraint                           | D     | 2059 |     |      |       |      |
| Unconstrained parking (PR > 1)               |       |     |     |      |       |      |
| Constrained parking (PR ≤ 1)                 |       |     |     |      |       |      |
| Development type                             | D     | 2059 |     |      |       |      |
| Single-family                                 |       |     |     |      |       |      |
| Multifamily                                   |       |     |     |      |       |      |
| Percent retail employment<sup>c</sup>        | BG    | 2070 | 0.00| 0.91 | 0.10  | 0.14 |
| Ratio job accessibility (transit to auto)<sup>d</sup> | BG    | 2070 | 0.00| 0.97 | 0.04  | 0.05 |
| Place Type                                    | BG    | 2072 |     |      |       |      |
| Urban Core                                    |       |     |     |      |       |      |
| Urban District                                |       |     |     |      |       |      |
| Urban Neighborhood                            |       |     |     |      |       |      |
| Suburban Neighborhood                         |       |     |     |      |       |      |
| Non-Urban                                    |       |     |     |      |       |      |

<sup>a</sup>HH Household; <sup>b</sup>D Development; <sup>c</sup>BG block group
<sup>d</sup>Derived using estimates from Chester et al. (2015) and CoStar data
<sup>e</sup>Derived from LEHD LODES 2017 Workplace Area Characteristics (WAC) for California
<sup>f</sup>Derived from University of Minnesota Accessibility Observatory: Transit Access 2017 and Auto Access 2018 (http://access.umn.edu/data/datasets/); Three households in Suburban Neighborhood place types exhibit ratios > 0.90. Excluding these households, max ratio accessibility is ~0.12. Because these households are missing information for other variables used in our models, they end up being excluded from our analysis
Household size and income (ordinal) information from the NHTS are also used in this analysis. We define household income as the midpoint of each household’s income category. Individual-level employment characteristics from the dataset are used to create dummy variables for zero-worker households and households where all individuals indicate they often telecommute. Additional variables control for each household’s survey day of the week and time of year, where the latter differentiated summer (June, July, August) and winter (November, December) months from the rest of the year to account for seasonal travel variation.

As discussed in the methods, the vehicle ownership and commute distances are Level 1 (Cost) dependent variables. Household vehicle ownership information was extracted directly from the NHTS data. Following the example of Crane and Boarnet (2001), we originally tested the travel “cost” of distance to work as a key Level 1 outcome variable to describe mileage-based variable costs. Commute distances were estimated as a function of the surrounding environment and regional location but did not include social demographic variables. However, 10% of households in the sample (N= 209) were missing commute distance information for all members. Predicted commute distances in the Level 2 VMT models provided limited significance and improvement in the model. For parsimony, we removed this Level 1 (Cost) analysis of commute distances. However, future work may include exploring the contribution of distances to work and/or school in explaining household- or individual-level VMT. To control for household worker characteristics, binary variables indicating whether a household had no workers and whether everyone in the household usually worked from home were included in the Level 2 VMT models.

The standard NHTS add-on data does not differentiate between multifamily and single-family dwelling structure types. These structure types are commonly used to segment the evaluation of the two scales of residential development in practice (Howell et al. 2018; Tian et al. 2018). Data differentiating between the two dwelling types was purchased and appended from M-S-G, a third-party company consulting for the NHTS and Caltrans.

The built environment: place types and accessibility

In this study, we apply the 2017 NHTS add-on place types, developed originally by Clifton and Gehrke (2016) as categorical measurements of the built environment and corresponding urban context of household locations. These place types describe variation of the built environments on a continuum of location-efficiency characteristics commonly known to influence travel behavior. These characteristics, often referred to as the “D’s”, are associated with decreased vehicle use and include density, diversity in land uses, design of street networks, destination accessibility, and distance to transit (Cervero and Kockelman 1997; Boarnet 2011; Handy 1992). Each block group is categorized in one of five location-efficient place types (Non-Urban, Suburban Neighborhood, Urban Neighborhood, Urban District, and Urban Core) based on its corresponding: population density, employment density, street intersection density, percentage of single-family housing, jobs within a half-mile of fixed-transit service, and jobs reachable within 45-min auto travel.

These place typologies have been applied in travel behavior research to examine the relationship between the residential environment and trip making (Howell et al. 2018; Clifton et al. 2018). While continuous measures of the built environment are often strongly correlated with travel, it can also be challenging to discern the effect of a single unit increase of such measures means for travel. Thill and Kim (2005) demonstrated that each operationalized measure or “D” captures just one facet of the larger concept, and no single
measure has greater predictive power than another. In this study, we also posit that there are certain thresholds of interrelated built environment characteristics where synergies occur and travel patterns shift. For example, the impact of one additional person, bus stop, or job offered in a square mile may be marginal, but substantial steps in multiple built environment variables may move the travel demand needle in clearly recognizable ways.

We also test two related accessibility measures as proxies for travel costs in our model framework. In CBC’s original work, the Level 1 (Cost) models include estimates of typical travel speeds or distances from the observed households, similar to our commute cost approach. More recently developed accessibility measures that capture opportunities within travel times are strong representations of the costs (and benefits) of travel within the neighborhood (Thill and Kim 2005; Crane and Boarnet 2001). The net effect of travel opportunities and costs on VMT is ambiguous (Crane 1996), making it an important control variable. Both automobile and transit accessibility are highly correlated with the place types, thus causing multicollinearity effects. We consider the ratio of transit accessibility to auto accessibility a useful metric to explore the influences of improved transit access to destinations because it distinguishes high-auto access, low-transit access areas (expected to be more auto-oriented) from high-auto access, high-transit access areas (expected to be more multimodal). These auto/multimodal indicators may vary within our place types, thus influencing decisions to use automobiles. Additionally, the percent of block group employment that is retail is used to capture variation in local non-work opportunities for households, representing nearby opportunities and attractiveness (Thill and Kim 2005).

**Residential parking estimates and assumptions**

Few cities have a comprehensive picture of off-street parking supply for private developments of any type of land use. While previous work suggests historical parking requirements may be an adequate approximation for parking supply (Chester et al. 2015), more recent work considering multifamily development over the last decade suggests that the actual on-site parking to be much more variable (Stangl 2019). Compared to single-family detached development, multifamily residential is often in denser areas and subject to reduced parking provisions (or density bonuses) that diverge from standard parking ratios.

To estimate off-street residential parking supply, we rely on a two-pronged approach. First, for single-family households, we apply the assumption-based methods used in Chester et al. (Chester et al. 2015). In this approach, Chester et al. summarize historic parking provision to make assumptions about the parking supply based on the age of development: one space per dwelling unit for pre-1936 development; two spaces for developments between 1936 and 1960; and three spaces for any development post-1960. However, the NHTS coordinates of each household link to the street network and not a specific parcel. Therefore, we identify the nearest single-family parcel using LA County’s parcel data and apply Chester et al.’s parking supply ratios based on the age of developments on that parcel—a reasonable assumption gives the county-wide pattern of nearby parcels being developed around the same point in time.

Second, for multifamily households, we estimate off-street parking supply using the national and proprietary CoStar commercial real estate database during the spring of 2020. While it is not an exhaustive database, it is the predominate source of commercial rental data in the US, and it is used frequently in practice by real estate agents. For every multifamily household observed in the travel survey, we first identify the nearest multifamily development address within the Los Angeles County’s parcel data. We then search the
CoStar database for the corresponding address. If the address nearest to the NHTS coordinate is not listed within CoStar, we examine the nearby developments that have a similar age and size. In most examined cases, the parking ratios of similar adjacent multifamily developments were observed to be nearly the same. In cases where no data were available for similar development within roughly a quarter mile, we do not append an estimate.

In line with our discussion of built environment data, we hypothesized that the effect on vehicle ownership of a single-unit change in parking ratio would be difficult to determine. We therefore decided to model parking supply as a binary variable with two levels: constrained and unconstrained parking ratio (parking spaces per dwelling unit). We tested both this two-level variable, with constrained parking being defined as households with a parking ratio of one or less, and a three-level variable, which added an additional level differentiating households with more than two spaces per dwelling unit. However, this additional “threshold” was not significant, suggesting only more constrained parking situations are statistically important to vehicle ownership.

Results and discussion

In this section, we present our results in three parts. First, we present our Level 1 (Cost) vehicle ownership model, highlighting the relationships between the outcome variables with parking constraints, the built environment, and demographics. Second, we present the findings from the Level 2 (Demand) models (total and homebased-work VMT), which include the predicted values from our cost models. Since we use a two-step approach, it is difficult to estimate the impact of constrained parking included in Level 1 (Cost) on VMT in Level 2 (Demand). Therefore, we apply our models predictively to illustrate a series of scenarios explaining the sensitivity of VMT towards parking supply across different place types.

Level 1 (Cost): Vehicle ownership

In the first step of our model framework, we estimate our Level 1 (Cost) models. Results of the vehicle ownership regression is provided in Table 2. In the vehicle ownership model, exponentiated coefficients are interpreted as a measure of effect size, where \( \exp(\beta) < 1 \) indicates a negative relationship and \( \exp(\beta) > 1 \) indicates a positive relationship.

With respect to vehicle ownership, the results show some degree of significance for each independent variable. Constrained parking is a significant and negative predictor of vehicle ownership, controlling for built environment place type. Households with unconstrained parking conditions (i.e., parking ratio > 1) are estimated to own 1.14 times more vehicles than households with constrained conditions (i.e., parking ratio ≤ 1). We also explore potential interaction effects between parking constraints with place and development types, testing the hypothesis that parking constraints have variable effects depending on urban context (e.g., transit availability, density, accessibility). However, there is not enough statistical power to identify significant and variable relationships. This is likely an artifact of the survey sampling strategy used and small samples sizes for each interacted category.

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6 For a brief discussion on place type and parking constraint interactions, see Post-Hoc Analysis.
Place and development types are both significant predictors of household vehicle ownership. Households in single-family developments are predicted to own 1.17 times as many vehicles as their multifamily counterparts. We estimate that households living in Urban Neighborhoods, Suburban Neighborhoods, and Non-Urban place types tend to own 1.29, 1.35, and 1.40 times as many vehicles, respectively, compared with households living in the Urban Core. There is not enough statistical power to detect a significant difference in vehicle ownership between those living in Urban District places and those in the Urban Core place type. Additionally, there is a small sample size of households in Non-Urban place types, which we included to control for exurban differences, but the coefficient should be interpreted with caution. We tested the stability of the parking constraint indicator by removing all other variables, one at a time, as well as alternative specifications for

| Variables                          | β    | exp(β) | p-value |
|-----------------------------------|------|--------|---------|
| (Intercept)                       | -0.36|        | 0.013   |
| Household size                    | 0.4  | 1.49   | <0.001 ***|
| Household size squared            | -0.04| 0.97   | <0.001 ***|
| Household income ($10,000s)       | 0.01 | 1.01   | <0.001 ***|
| Parking constraint                |      |        |         |
| Unconstrained parking             | Reference |      |         |
| Constrained parking               | -0.13| 0.88   | 0.004 **|
| Place Type                        |      |        |         |
| Urban Core                        | Reference |      |         |
| Urban District                    | 0.19 | 1.21   | 0.157   |
| Urban Neighborhood                | 0.26 | 1.29   | 0.041 * |
| Suburban Neighborhood             | 0.3  | 1.35   | 0.019 * |
| Non-Urban                        | 0.34 | 1.40   | 0.052 ..|
| Development type                  |      |        |         |
| Single-family                     | Reference |      |         |
| Multifamily                       | -0.16| 0.86   | 0.001 ***|

Observations: 2,001  
R² Nagelkerke: 0.42 
Deviance: 901  
AIC: 5,681  
log-Likelihood: -2,829*

Notes:  
Model form: NB = Negative binomial; unweighted  
R² Nagelkerke  
*Log-Likelihood ratio test with intercept-only model: $\chi^2(9) = 463.82$, p < 0.001  
.. p < 0.1  * p<0.05  **p<0.01  ***p<0.001
Both income and household size (e.g., log transformations). The parking constraint coefficient estimated remained largely unchanged—estimated exp(β) between 0.86 and 0.89—and the significance remained high (p-value < 0.01).

Not surprisingly, household demographics are significant predictors of vehicle ownership, and their effects are in the expected directions. The negative coefficient estimated for the square of household size reveals a diminishing effect for each additional household member on vehicles owned. While we control for demographics here, it is important to note that demographics are not typically incorporated when evaluating the transportation impacts of development in practice (Currans et al. 2020a). In their best practices for traffic impact assessments, McRae et al. (2006) argues that the demographic makeup of a neighborhood is likely to change drastically over the lifespan of any one development, and therefore should not be included. However, controlling for demographics allows us to parse out the relationships with income and household size, both consistently found to be strong predictors of both vehicle ownership and use. Determination of formal guidelines for how to consider demographics for development review is an important area for future research and consideration.

### Table 3  Level 2 (Demand) models: total and homebased-work VMT

| Predictors                        | Model 1: Total VMT | Model 2: Home-based Work VMT* |
|-----------------------------------|--------------------|------------------------------|
|                                  | B                  | ME b                         | p-value | B                  | ME b                         | p-value |
| Intercept                        | 2.67               | 0.638                        | 0.01    | -1.27              | 0.77                         |        |
| Vehicle ownership (predicted)    | 23.4               | 17.35                        | <0.001  | 8.48               | 3.33                         | <0.001  |
| Percent retail employment        | 3.75               | 2.78                         | 0.68    | -1.12              | 0.44                         | 0.89    |
| Ratio accessibility (transit to auto) | -176.03          | -130.53                      | <0.001  | -120.28            | -47.17                       | <0.001  |
| Telecommuter household           |                    |                               |         |                    |                              |         |
| Non-Telecommuter household      | -2.74              | -2.03                        | 0.65    | -28.05             | -10.99                       | <0.001  |
| Telecommuter household           |                    |                               |         |                    |                              |         |
| Has workers                      | Reference          |                               |         | Reference          |                              |         |
| No workers                       | -20.95             | -15.53                       | <0.001  | -93.44             | -36.65                       | <0.001  |
| Travel day                       |                    |                               |         |                    |                              |         |
| M - Th                           | 3.01               | 2.23                         | 0.43    | -5.98              | -2.35                        | 0.02    |
| Sat/Sun                          | -0.04              | -0.03                        | 0.99    |                    |                              |         |
| Travel month                     |                    |                               |         |                    |                              |         |
| Other months                     | Reference          |                               |         | Reference          |                              |         |
| Summer months                    | -1.63              | -1.21                        | 0.59    | 1.1                | 0.43                         | 0.65    |
| Winter months                    | 0.34               | 0.26                         | 0.92    | 3.88               | 1.52                         | 0.17    |

Observations: 1,999<sup>a</sup> 1,440<sup>b</sup>

Notes:
- Tobit, unweighted
- HRW VMT estimates based on sample households surveyed on weekdays only
- Marginal effects represent the change in VMT for a one-point change in a predictor, when all independent variables are set to their mean value. Marginal effects are also depicted as a barchart here. The effect for Ratio Accessibility was large, and therefore is not depicted relatively to observe effects of the rest of coefficients.
- Left-censored: 245; Uncensored: 1,754
- Left-censored: 651; Uncensored: 789
- Log-Likelihood ratio test with intercept-only model: χ²(9) = 292.42, p < 0.001
- Log-Likelihood ratio test with intercept-only model: χ²(8) = 624.28, p < 0.001
- Predicted from Table 2 model estimating vehicle ownership
- *p<0.05  **p<0.01  ***p<0.001
Level 2 (Demand): Total and homebased-work VMT

The summaries for our Level 2 (Demand) models—both total and homebased-work VMT—are provided in Table 3. Tobit regression provides estimates relative to an uncensored latent variable. For interpretation, we include marginal effects to demonstrate the difference in VMT, on average, for a one-unit increase in the value of a continuous predictor. For categorical explanatory variables, the marginal effects express the difference in VMT, on average, relative to the reference class. For Tobit regressions, marginal effects are estimated at the mean sample value for each coefficient.

Not surprisingly, predicted vehicle ownership is a significant and positive predictor of both total and homebased-work VMT. For every additional vehicle in the average household, we estimate the household travels approximately 17 more miles of total VMT and 3 more miles in home-based work VMT. We tested the stability of the vehicle ownership coefficients in both the total and homebased-work VMT models by testing the models with and without each of the variables and comparing effect sizes and significance levels. This resulted in a range of coefficient values for 23–28 for total VMT and 8–11 for homebased-work VMT with consistent significance levels.

Household worker characteristics are significant determinants of both total and homebased-work VMT. Compared to households with at least one worker, zero-worker households are predicted to drive approximately 15 fewer total miles per day and 36 fewer homebased-work miles, on average. Telecommuter households also drive significantly less homebased-work VMT than non-telecommuter households, approximately 11 miles less on average. For this sample, less than 10% of households telecommuted. It is important to note that these data were collected in 2017 prior to the start of the COVID-19 pandemic. Since then, tastes and preferences for telecommuting and corresponding vehicle ownership and use may have changed or continue to evolve in response to pandemic-related social distancing measures that promote telecommuting. This is an important area for future research. Other demographic characteristics used in the Level 1 (Cost) models (i.e., household size, income) were not incorporated due to multicollinearity issues introduced by including predicted vehicle ownership. Based on our framework, household size and income are more likely to influence medium or long-term decision making about vehicle ownership and costs, while current employment status and telecommuting are more likely to influence day-to-day travel. Long-term unemployment may also influence vehicle ownership decisions, but this information is not readily captured in the travel survey studied here.

Post-hoc analyses

In this section, we provide two secondary analyses to dive further into different aspects of our model framework and previously presented results. First, we evaluate the hypothesis that the effect of parking on VMT is mediated through vehicle ownership through two approaches. Second, we develop a series of scenarios to evaluate the sensitivity of VMT to constrained parking.
Evaluating mediation effects

Turning to the mediation analysis, we see Step 1 to be true in the vehicle ownership model presented in Table 2: constrained parking is a significant predictor of vehicle ownership. To evaluate the subsequent steps, we must test the (Step 2) significance of parking predicting VMT and (Step 3) vehicle ownership predicting VMT while controlling for parking. Here, we present aggregate models of total and home-based work VMT regressed on observed values included in both Level 1 and Level 2 models in Tables 4 and 5. For both total and home-based work VMT, we present an aggregate model without vehicle ownership (to evaluate Step 2) and with vehicle ownership (to evaluate Step 3).

Looking at the regressions in Tables 4 and 5 that exclude vehicle ownership for total and home-based VMT, constrained parking is a significant predictor for total VMT, but not home-based work VMT. However, once vehicle ownership is added to these regressions, it
remains significant for total VMT, and the effect size of constrained parking is minimized for both total and home-based-work VMT. Overall, these results support a mediation effect of parking on VMT through vehicle ownership given both Step 1 and 3 of the Baron and Kenny (1986) approach are satisfied.

Next, we calculate the indirect effect of parking on VMT through vehicle ownership and test it for significance. Van Acker and Witlox (2010) utilize SEM to estimate and test both direct and indirect effects of their predictors on vehicle use outcomes, and find significant evidence for mediation. In their analysis, all five of the built environment variables exhibit a direct effect on vehicle ownership, but only one of the five exhibits a direct effect on vehicle use, along with vehicle ownership. Because we did not adopt an SEM framework, we rely on a bootstrapping approach with 5000 resamples described by Preacher and Hayes (2004) to test the indirect effect of parking on VMT through vehicle ownership for significance. In this approach for a dataset with N observations, 5000 samples of N observations

| Table 5 | Level 1 and Level 2 aggregate home-based-VMT models with and without vehicle ownership |
|---|---|
| **Predictors** | **With observed vehicle ownership** | **Without observed vehicle ownership** |
|  | B | ME | p-value | B | ME | p-value |
| Intercept | 7.04 | 0.46 | 12.29 | 0.2 |
| Vehicle ownership (observed) | 6.58 | -2.57 | <0.001 |
| Household size | -3.34 | -1.3 | 0.25 | 1.23 | 0.48 | 0.66 |
| Household size squared | 0.85 | 0.33 | 0.04 | 0.45 | 0.18 | 0.28 |
| Income ($10,000s) | 0.69 | 0.04 | 0.45 | 0.21 | 0.08 | 0.09 |
| Telecommuter household | Reference | Reference |
| Non-Telecommuter household | Reference | Reference |
| Commuter household | -27.4 | -10.68 | <0.001 | -27.68 | -10.86 | <0.001 |
| Zero worker household | Reference | Reference |
| Household has workers | Reference | Reference |
| No worker household | -92.11 | -35.91 | <0.001 | -92.91 | -36.47 | <0.001 |
| Development type | Reference | Reference |
| S | 1.96 | 0.76 | 0.47 | 0.76 | 0.3 | 0.78 |
| M | 1.96 | 0.76 | 0.47 | 0.76 | 0.3 | 0.78 |
| Parking constraint | Reference | Reference |
| Unconstrained parking | Reference | Reference |
| Constrained parking | -1.65 | -0.64 | 0.53 | -3.18 | -1.25 | 0.23 |
| Percent employment that is retail | -2.25 | -0.88 | 0.77 | -1.73 | -0.68 | 0.82 |
| Ratio accessibility (transit to auto) | -103.18 | -40.23 | 0.01 | -124.06 | -48.7 | <0.01 |
| Place Type | Reference | Reference |
| Urban Core | Reference | Reference |
| Urban District | -6.47 | -2.52 | 0.38 | -6.09 | -2.39 | 0.41 |
| Urban Neighborhood | -2.22 | -0.87 | 0.76 | -2.21 | -0.87 | 0.76 |
| Suburban Neighborhood | -1.78 | -0.69 | 0.82 | -1.53 | -0.6 | 0.85 |
| Non-Urban | 4.23 | 1.65 | 0.72 | 5.25 | 2.06 | 0.66 |
| Travel day | Reference | Reference |
| M – Th | Reference | Reference |
| Fri | -5.81 | -2.27 | 0.02 | -6.17 | * -2.42 | 0.02 |
| Sat/Sun | Reference | Reference |
| Travel month | Reference | Reference |
| Other months | 1.03 | 0.4 | 0.67 | 1.09 | 0.43 | 0.65 |
| Summer months | 3.59 | 1.4 | 0.19 | 3.88 | 1.52 | 0.17 |
| Winter months | 1.440 | 1.440 | 0.37 | 0.36 | 8.293 | 8.328 |
| Observations | 1.440 | 1.440 | 0.37 | 0.36 | 8.293 | 8.328 |

Notes:
- Marginal effects represent the change in VMT for a one-point change in a predictor, when all independent variables are set to their mean value. Marginal effects are also depicted as a bar chart here. The effect for Ratio Accessibility was large, and therefore is not depicted relatively to observe effects of the rest of coefficients.
- p < 0.1 * p < 0.05 ** p < 0.01 *** p < 0.001 ; unweighted
are built with replacement, and the indirect effect is repeatedly tested for significance. Results of this analysis are summarized in Table 6.

Results in Table 6 generally echo those explored using the Baron and Kenny (1986) approach, with some additional insight. Note that while significant indirect effects exist for both total and homebased work VMT, there is significance for the direct effect only for total VMT. This finding aligns with the results of the aggregate models presented in Tables 4 and 5. The results presented in Table 6 provide evidence to support that the impact of parking on total VMT is partially mediated by vehicle ownership, while the impact of parking on homebased-work VMT is fully mediated by vehicle ownership, although in the case of the latter, the total effect of constrained parking is not significant. This indicates that constrained parking may have a more significant impact on homebased non-work VMT than work VMT.

**Scenario analysis: how sensitive is VMT to parking?**

To further explore the relationship between parking and VMT by place type, we first use Level 1 and Level 2 models together to develop a suite of scenarios for typical households in Los Angeles County. Then, we present VMT estimates for a hypothetical 100-unit development, comparing three different parking constraint scenarios.

To build the scenarios in Fig. 4, we estimated VMT for both constrained and unconstrained parking scenarios across place types. Additionally, we re-estimated the vehicle ownership model in Table 2 without parking constraint and carried forward predicted values to estimate VMT in this case as well. This allows for more robust comparisons of our model estimates with other predicted VMT tools that do not consider parking as it provides relative values to adjust these outputs to reflect sensitivity to parking constraint.

The scenarios in Fig. 4 depict the proportion of VMT for each place type and parking constraint scenario relative to the predicted VMT for a household in a Suburban Neighborhood, not controlling for constrained parking. Place type and parking constraint were the only two variables changed; all other variables are applied using the Los Angeles

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Here, we exclude Non-Urban results given the small sample size for households in this category; for this reason, we caution use of results for Non-Urban settings.
County average, thus representing a “typical” household. The average demographic characteristics are from the American Community Survey (2017, 5-year), and the percent retail density estimate is from the Longitudinal Employer-Household Database (2017, workplace area characteristics, LODES). The average ratios of accessibilities are from the full accessibility dataset from the county (see footnotes in Table 1). These scenarios allow us to compare—in broad terms—the relative differences that place and parking have on estimates of VMT. In future work, it would be valuable to study the scenario predictions exploring the relative impacts of parking and place with more location-sensitive demographics.

For all scenarios in Fig. 4, estimates for VMT where parking is not considered lie somewhere between those predicted for constrained and unconstrained parking cases. The constraint of parking accounts for an approximate 4–10 percentage-point decrease in total VMT within each place type, compared to VMT estimates where parking is not considered. Total VMT estimates for unconstrained parking scenarios reflect an approximate 3–6 percentage-point increase compared to estimates not controlling for parking constraint.
The estimated relationship between constrained parking and home-based work VMT is even steeper, associated with an 8–21 percentage-point decrease in home-based work VMT compared to estimates where parking is not considered. Further, unconstrained parking scenarios reflect an approximate 6–12 percentage-point increase in home-based work VMT compared to estimates not controlling for parking constraint. While we expect VMT to decrease in more urban contexts, the act of constraining parking appears to reduce household vehicle demand to nearly the same rate as households in a slightly more urban place type. We found the interaction terms between parking constraint and place type to be insignificant in the vehicle ownership model presented in Table 2, perhaps due to sample size constraints.

Next, we explore three scenarios for a hypothetical, 100-unit multifamily development located in an Urban District. We assume each household is comprised of two individuals and earns the median income for Los Angeles County, taken from the American Community Survey (2017, 5-year). We take the average values across Los Angeles County’s Urban District block groups for the ratio of transit to auto job accessibility and percent retail employment from the same sources described above. No households are telecommuter or zero-worker households, and VMT is estimated for a typical day Monday through Thursday, not during summer (June, July, August) or winter (November, December) holiday months.

In the first scenario, we assume each household has two parking spaces (therefore, each household is classified as having unconstrained parking). In the second scenario, we assign half of the households two parking spaces, and the other half just one parking space (therefore, half of the sample is classified as having constrained parking, and the other half is classified as having unconstrained parking). In the third scenario, we assume each household has only one parking space (therefore, each household is classified as having constrained parking). Estimates for total and home-based work VMT are presented in Fig. 5. Actual VMT estimates are provided in the top panel of Fig. 5, while relative estimates are provided in the bottom panel. For the relative estimates,
the baselines for total VMT and homebased-work VMT are the respective scenarios for each where all 100 units have unconstrained parking.

Results indicate that constraining half of the households’ parking would decrease total VMT by seven percentage-points and homebased-work VMT by eight percentage-points, compared to the scenario where all households were allotted two parking spaces. When all of the households’ parking is constrained, these effects approximately double, as expected; constraining all households’ parking would decrease total VMT by 13 percentage-points and homebased-work VMT by 16 percentage-points, compared to the scenario where all households were allotted two parking spaces. Currans et al. (2020a, b) note that vehicle impacts of individual households may seem small, but that effect sizes aggregated up to a development are more pronounced. Extending this logic, the VMT impacts of multiple developments similar to our hypothetical 100-unit example situated in the same neighborhood can quickly aggregate to form substantial area-wide transportation impacts.

Conclusions

In this paper, we have established evidence that off-street residential parking supply is related to vehicle travel demand (e.g., VMT), and that relationship is mediated through vehicle ownership. In our two-step approach, we estimated the vehicle transportation costs in Level 1. These include the fixed costs associated with vehicle ownership—a function of household demographics, place type, and parking. In Level 2, we associate these costs as well as employment controls (unemployed and teleworking households) and measures of local urban context (retain employment and transit accessibility as a proportion of vehicle accessibility) with demand in VMT. Here, we reflect on the implications of these findings for practice and research, and we outline potential areas of future work.

In this study, we offer an initial framework to address this issue. Our two-step model framework helps establish a nexus between parking and VMT, which is supported more robustly by our post-hoc mediation analysis. This mediation analysis demonstrates statistically that the effect of parking on VMT is mediated through vehicle ownership. The regression equations derived from our models can be used to build a user-friendly, practical tool for practitioners, where inputs can be adjusted to control for local context to establish the relationship between parking and VMT for a particular study area or development.

In one of our post-hoc tests, we explicitly test for a mediation effect of constrained parking on VMT through vehicle ownership. We found the indirect effect of constrained parking, as mediated through vehicle ownership, on both total and homebased-work VMT to be significant. This suggests the influence of both Level 1 and Level 2 indicators is most relevant in household vehicle ownership decision-making, as indicated through van Acker’s work (Van Acker and Witlox 2010). To implement effective policies for meeting regional or neighborhood goals, however, we must better understand the pathways by which off-street parking influences travel demand through both long- and short-term household decision making, as research suggests it does (Weinberger 2012). With that, this study does have limitations. Primarily, while we identified a significant mediated effect, this is not yet enough information to determine causality overall. Note, however, that the purpose of this work was not to establish causality, and as such, the model specifications were not designed to do so. We did not have the ability to test for self-selection bias in this study. It is likely that, to some degree, households self-select developments according to their needs—car owners looking for developments with adequate parking; non-car owners selecting housing
with unbundled parking for cheaper rates. Similarly, many developments may market to households with specific socio- or economic-characteristics that may be linked with differing vehicle use behaviors. Additionally, by customizing the specification of this approach to more directly be applied in practice, we are not able to test the indirect pathways and relationships, as explored in the foundational van Acker and Witlox (2010) discussed in the background. In this study, both types of pathways are considered in our conceptual framework (Fig. 1), but neither are addressed in full in our analysis. Existing large-scale, household travel surveys may not alone provide the nuance of information necessary to explore these questions in detail. Future studies would benefit from customized survey instruments inquiring about preferences and decision-making processes at the individual- and household-levels. Studies taking advantage of more random processes of residential selection—such as the residential lottery study by Millard-Ball et al (2021)—provide strong tests of the causality of vehicle parking on demand.

In the current state of the literature, a number of studies exploring VMT have “controlled” for parking through built environment measures. Off-street parking, as a data source, is limited, incomplete, and difficult to synthesize. For example, the price of parking varies from development to development; parking requirements often serve more as guidelines than strict standards (Stangl 2019); and the various ways that parking management mechanisms or pricing can be implemented add an additional layer of complexity to analyses. In response, we often see dummy-variable proxies for constraints like how difficult it is to park (van Acker and Witlox 2011), parking convenience (Guo 2013), or general supply of parking garages in an area (Cao et al. 2007). Several authors in this area of work note the importance of parking (Ewing Reid et al. 2011), but many more are satisfied using built environment characteristics as proxies for parking constraints more broadly (Ewing Reid et al. 2011; Van Acker et al. 2007; Cervero and Murakami 2010; Chatman 2008).

For too long, parking has been relegated to proxies in travel demand research. To understand the effect of vehicle travel through land use, we must incorporate off-street parking supply into analyses exploring the influence of the built environment. Without explicit controls—and an understanding of how to effectively consider those controls in analysis and practice—studies that do not incorporate parking ignore a major element of the built environment. This leaves a critical gap in cases where parking supply does not align well with conventional expectations, such as with developers building large underground parking garages in urban centers and thus ignoring a potential policy lever. We found that off-street residential parking supply was only somewhat correlated with built environment in this analysis. For multifamily developments, parking supply was negatively correlated with our decreasingly urban place types (Kendall’s rank tau = 0.13, p-value < 0.01) and negatively correlated with transit accessibility (Pearson’s product-moment correlation = −0.18, p-value < 0.01). In fact, through iterative testing, we continue to find no issue incorporating built environment measures or place types alongside parking supply in our model tests (using VIF as an indicator). In other words, the correlations are not nearly strong enough to “proxy” parking constraints or justify outright exclusion due to multicollinearity.

**Future work**

Beyond what has already been stated, one important area of future work may test the effects of parking at destinations (including workplace and neighborhood locations) for vehicle ownership and/or travel tied to the home, given the emerging evidence of their influence. For example, work by Clifton et al. (2020) suggests that even developments
with no off-street parking have development-level impacts on the surrounding neighborhood (including from both personally owned vehicles and car/ride share). Further, Shin (2020) provides evidence that free or subsidized workplace parking is associated with VMT increases that spill over to non-work trips. Moreover, parking provisions are closely tied to the ability to develop density—as Manville et al (2013) discuss, the issues related to redeveloping parking inhibit desires to increase housing and destination accessibility. More localized and qualitative evaluations on the municipal processes which constrain the development of housing and destinations are needed.

Another area of exploration involves examining relationships between VMT and other parking-related measures. For example, data that assess personal individual thresholds for parking pricing would be useful to explore parking pricing as an additional lever for curbing VMT. Further, vehicle ownership and parking supply might be considered jointly to estimate parking utilization (or turnover) at a given development to glean implications for VMT. Studies undertaken for King County, WA (Rowe et al. 2014) and Washington, D.C. (Rogers et al. 2016) provide recent examples for estimating parking utilization at residential developments. In both studies, parking utilization was defined as a ratio of observed vehicles parked overnight to total parking spaces available. Results from these analyses demonstrate significant relationships exist between both parking supply and pricing measures with parking utilization. However, the potential relationship between parking utilization and VMT is ambiguous. A single-point measure of parking utilization says little about what trip making occurred during the day. Rather, parking utilization might be estimated at intervals throughout the day to compute hourly turnover rates, which might be more explicitly tied to development-level VMT.

There are two key areas of work that could help close the parking gap in research, and off-street parking policies and management at large. First, household travel surveys should incorporate questions about residential and neighborhood parking constraints. These questions should elicit the residential parking availability for each household, whether housed on-site or off, and monetary costs for each space. Additionally, with a few extra questions, travel surveys could also inquire about workplace location parking constraints (e.g., cost, supply, ease, timing). While many surveys already ask about attitudes, preferences, or frequencies of active or transit travel, questions that explore the dependence of parking could enable researchers to better link parking availability at retail and service establishments with residents in the area. Second, a coordinated national effort to inventory off-street parking supply would enable researchers to include parking as a critical built environment factor in travel behavior studies. Advances in artificial learning technologies and computer processing could facilitate vast improvements in data collection for cities across the US and beyond.

In any case, collecting more information about parking is the first step, albeit a challenging one, to advancing our understanding and thus our ability to manage off-street parking requirements and aligning parking with vehicle travel, and therefore our travel (and emissions) goals and targets.

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Declarations

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