METHODS

Variable Construction

Dependent Variables

After manually adjusting discrepancies attributed to data collection and survey reporting in the combined Phase I and II data, the creation of two outcome variables (parking demand and parking utilization) was undertaken. For this study, *parking demand* was defined as the count of overnight vehicles per count of occupied housing unit. The numerator is the sum of observed parked cars in surface lot or garage spaces at a particular multifamily housing (MFH) building as tallied by MAPC staff, while the denominator is the number of units with a tenant in the MFH building as reported by surveyed building staff. In instances where this information was not reported (n=7), US Census tract-level MFH vacancy rates from the 2013-2017 American Community Survey were applied to the reported total number of units. *Parking utilization*, in turn, was defined in this study as the count of overnight vehicles per count of vehicle parking spaces.

Independent Variables

To identify the predictors of parking demand and utilization, a set of site-specific variables describing the MFH structure and its available parking features as well as locational attributes pertaining to the building's surrounding built environment and socioeconomic context were created (**Table 1**).

Table 1. Definition of independent variables.

Variable	Description
Building Features	
bldg_affp	Share of housing units in multifamily complex that are affordable (subsidized)
bldg_agec_1	Multifamily complex was constructed before 1946
bldg_agec_2	Multifamily complex was constructed between 1946 and 2000
bldg_agec_3	Multifamily complex was constructed after 2001
bldg_bed_unit	Average count of bedrooms in housing unit of multifamily complex
bldg_cost_room	Average monthly cost (US $) of housing unit in multifamily complex per bedroom
bldg_cost_unit	Average monthly cost (US $) of housing unit in multifamily complex
bldg_szec_1	Multifamily complex with less than 25 housing units
bldg_szec_2	Multifamily complex with between 25 and 100 housing units
bldg_szec_3	Multifamily complex with at least 100 housing units
bldg_ten_rnt	Tenure of housing units in multifamily complex (0=owner-occupied, 1=renter-occupied)
Parking Features	
park_bike	Presence of indoor bicycle parking at multifamily complex
park_cost	Average monthly cost (US $) of first parking space at multifamily complex
park_cost_room	Ratio of monthly parking cost of first parking space to monthly cost per bedroom
park_cost_unit	Ratio of monthly parking cost of first parking space to monthly cost per housing unit
park_garp	Share of total parking spaces that are located in a parking garage
park_gl_bal	Ratio of garage parking spaces to lot parking spaces
park_sup	Count of vehicle parking spaces per count of occupied housing units
Built Environment	
b_umn_t30jobs	Cumulative employment accessible from US Census block in a 30-minute transit trip
bg_act_den	Persons and employment per acre in US Census block group
bg_emp_den	Employment per acre in US Census block group
bg_pop_den	Persons per acre in US Census block group
mbta_crail	MBTA commuter rail station within half-mile aerial buffer of multifamily complex
mbta_rapid	MBTA rapid transit station within half-mile aerial buffer of multifamily complex
walk_score	Walk Score attributed to the multifamily complex

Socioeconomic Context	
ct_inc_med	Median annual income for households in US Census tract
ct_sze_own	Average household size of owner-occupied housing units in US Census tract
ct_sze_rnt	Average household size of renter-occupied housing units in US Census tract
ct_tenp_rnt	Share of households in US Census tract who reside in a renter-occupied housing unit
ct_vehp_0	Share of households in US Census tract with zero vehicles available

Building feature metrics were constructed using responses from a two-page survey provided by property managers and owners, with the exception of building age which was determined using MassBuilds data. The three cost variables were created using a representative value found within the categorical response. For example, if a property manager noted that a 1 bedroom apartment rented for between $1,000 and $1,499, then the average monthly rent for a 1-bedroom unit in that complex was $1,250. Parking feature metrics also used the property manager survey responses as well as the overnight data collection efforts by MAPC staff. Two of the parking cost metrics, which were normalized by a count of units and bedrooms found in the MFH complex, were weighted averages that incorporated imputed unit bedroom counts for occupied units when this distribution could not be gleaned from property manager responses (n=11). This imputation of values for records without a distribution of bedroom sizes within a complex was completed by applying sample distributions within the three building size categories.

Independent variables reflecting the built environment surrounding an MFH complex were constructed using a set of secondary data sources. Accessibility to employment opportunities via a 30-minute transit trip were derived from the University of Minnesota's Accessibility Observatory, which used 2017 data for morning peak period (7-9am) travel. The area-based density metrics were calculated at the Census block group, with population figures from the 2013-2017 American Community Survey 5-Year Estimates and employment figures from the 2015 Longitudinal Employer-Household Dynamics data set. Meanwhile, the binary variables describing the presence of an MBTA rapid transit or commuter rail station within a half-mile areal buffer around a building used location data from the General Transit Feed Specification (GTFS). Walk Score was calculated using an API call based on the geocoded location of the MFH site using Google Maps API. The five neighborhood-level socioeconomic context metrics were measured at the Census tract geography and also derived from the 2013-2017 American Community Survey 5-Year Estimates.

Model Development

With the created independent variables, a first analytic step was the estimation of single-variable linear regression models for parking demand and parking utilization. The resulting model associations described the direction, magnitude, and statistical significance of each predictor, which was then used to specify full models for the two outcomes of interest. For the next step, a base model was specified using a stepwise, forward selection process with building and parking features, where variables were sequentially added to the model based on their unadjusted association until a variable's addition was not statistically significant ($p > 0.10$). After establishing a base model, the process was repeated to assess the added benefit of built environment and socioeconomic variables, until interim and full models of parking demand and utilization were produced. Another set of models were next explored, which used the same model specification steps as noted above, but predictors transformed by square root and logarithmic methods based on variable distributions. The intention of this last set of models with variable transformations was to provide a path toward developing a model explaining as much variation in parking demand and utilization as possible. These models with transformed predictors are more difficult to explain, but useful if the development of a parking calculator was deemed desirable.

RESULTS

Descriptive Statistics

Table 2 provides the descriptive statistics for the aforementioned variables as well as results of the single-variable regression models of parking demand and parking utility. Looking at the coefficient (beta) values, an increased share of affordable housing units in an MFH structure had a negative association with parking demand and utilization. Other building and parking features with a significant and negative connection to parking demand included percent of rental units in structure and, importantly, two variables related to unbundled parking costs. In turn, an increase in parking supply and the average number of bedrooms per unit was linked to an increase in the number of overnight vehicles per occupied housing unit.

Table 2. Descriptive statistics and correlations with parking outcome variables.

						park_dem[a]		util_rate[b]	
Variable	n	mean	stdev	min	max	beta	p	beta	p
Parking Outcomes									
park_dem	189	0.73	0.34	0.02	1.73				
util_rate	189	0.72	0.17	0.09	1.00				
Building Features									
bldg_affp	189	0.29	0.38	0.00	1.00	-0.36	0.00	-0.14	0.06
bldg_agec_1	19	0.10							
bldg_agec_2	51	0.28							
bldg_agec_3	113	0.62							
bldg_bed_unit	189	1.61	0.41	1.00	2.80	0.15	0.03		
bldg_cost_room	142	1,279.33	584.65	357.14	3,000.00				
bldg_cost_unit	142	1,897.31	708.35	811.11	3,000.00				
bldg_szec_1	50	0.26							
bldg_szec_2	78	0.41							
bldg_szec_3	61	0.32							
bldg_ten_rnt	189	0.87	0.33	0.00	1.00	-0.22	0.00		
Parking Features									
park_bike	189	0.22	0.41	0.00	1.00				
park_cost	189	48.97	95.47	0.00	425.00	-0.16	0.03		
park_cost_room	142	0.03	0.05	0.00	0.19				
park_cost_unit	142	0.02	0.04	0.00	0.14	-0.15	0.07		
park_garp	189	0.32	0.44	0.00	1.00				
park_gl_bal	189	41.24	100.27	0.00	482.00				
park_sup	189	1.04	0.46	0.12	2.39	0.85	0.00		
Built Environment									
b_umn_t30jobs	189	129,579.49	157,475.22	2,697.00	666,769.00	-0.43	0.00	-0.15	0.05
bg_act_den	189	45.14	41.50	1.97	442.95	-0.32	0.00		
bg_emp_den	189	17.44	34.45	0.20	350.76	-0.22	0.00		
bg_pop_den	189	27.70	20.87	0.00	110.12	-0.27	0.00		
mbta_crail	189	0.35	0.48	0.00	1.00	-0.14	0.06		
mbta_rapid	189	0.44	0.50	0.00	1.00	-0.25	0.00	-0.13	0.08
walk_score	189	78.52	15.74	13.00	99.00	-0.42	0.00		
Socioeconomic Context									
ct_inc_med	189	68,877.25	30,322.05	17,305.00	210,639.00	0.23	0.00		
ct_sze_own	189	2.61	0.54	1.65	4.20	0.13	0.08	0.20	0.01
ct_sze_rnt	189	2.27	0.50	1.49	3.97	-0.12	0.10		
ct_tenp_rnt	189	0.64	0.17	0.15	0.97	-0.41	0.00		
ct_vehp_0	189	0.16	0.12	0.00	0.62	-0.55	0.00	-0.14	0.05

Somewhat surprisingly, each of the tested built environment features had a negative association with parking demand. In other words, independently, MFH structures in neighborhoods with a high density of residents and jobs as well as strong access to nearby amenities, rail-based transit stations, and increased regional accessibility to employment opportunities had fewer vehicles per occupied housing unit. In terms of parking utilization, sites within a short walking distance to a rapid transit station and with a high level of accessibility to regional jobs experienced lower levels of parking utilization.

As for the socioeconomic context of the Census tract, an MFH structure in an area with a higher median annual household income and average household size in owner-occupied units was associated with an increase in parking demand, with the latter predictor also being positively associated with parking utilization. In turn, MFH structures in Census tracts with a greater share of rental units and higher average household size per rental unit was associated with decreased parking demand. As expected, multifamily structures in a Census tract with a greater share of individuals with zero-vehicle households experienced lower levels of parking demand and utilization.

Model Estimation

Pivoting from the single-variable models discussed above, the results of sequential multivariate regression models of parking demand are provided in **Table 3**. Model 1 details the building and parking features that significantly predicted parking demand, but does not take into account its surrounding built environment (Model 2) or these physical features and its socioeconomic context (Model 3). The following paragraph describes the findings from Model 2, which reflects a full specification capturing many of the building and parking features as well as the physical siting characteristics that developers and planning officials may be more easily able to shape through zoning, policy, and more intentional decision-making.

Table 3. Predictors of parking demand (overnight vehicles per count of occupied housing units).

	Model 1[a]		Model 2[b]		Model 3[c]	
Variable	b	p	b	p	b	p
intercept	0.18	0.01	0.20	0.01	0.25	0.01
Building and Parking Features						
bldg_affp	-0.13	0.01	-0.08	0.03	-0.08	0.03
bldg_cost_unit (x 1,000)	-0.04	0.07				
park_sup	0.65	0.01	0.57	0.01	0.55	0.01
Built Environment						
b_umn_t30jobs (x 100,000)			-0.03	0.01		
Socioeconomic Context						
ct_vehp_0					-0.41	0.01

Notes: [a] Building and parking features; AIC = -108.23, R^2 = 0.78.
[b] Building, parking, and built environment features; AIC = -117.54, R^2 = 0.74.
[c] Building, parking, built environment, and socioeconomic context features; AIC = -119.38, R^2 = 0.74.

In our sample of nearly 200 sites, the provision of one additional parking space for an occupied housing unit resulted in an increase of 0.57 overnight vehicles per occupied housing unit being parked at an MFH site. An intuitive finding suggesting if developers of new MFH options continue to accommodate vehicle-oriented travel (i.e., increasing parking supply), then a result will be increased parking demand. However, this model found an increase in the percent of affordable units within an MFH complex and improvement in the accessibility of its residents to employment opportunities via a 30-minute transit trip decreased the demand for parking.

Of note, a similar model building process was undertaken to better understand the predictors of parking utilization; however, because of the poor performance of these models, their results are not presented. A likely reason for this outcome is that the dependent variable's denominator, reflecting parking supply, was the strongest predictor of parking demand, but could not be incorporated in the specification process.

Finally, **Table 4** shows the findings of a set of models with transformed predictors, which could be useful if the creation of a parking calculator was pursued. Model 4 reflects a specification using **Table 1** variables of parking, building, and built environment features with various transformations tested for each variable, while Model 5 included socioeconomic context variables (and their various transformations) and Model 6 started with the Model 3 specification and tested whether the addition of transformed variables improved this specification. As in the results of the first three models, the variation in parking demand remains best explained by parking supply within these latter three models.

Table 4. Transformed predictors of parking demand (overnight vehicles per count of occupied housing units).

	Model 4[a]		Model 5[b]		Model 6[c]	
Variable	b	p	b	p	b	p
intercept	0.48	0.01	0.13	0.01	0.18	0.01
Building and Parking Features						
bldg_affp					-0.08	0.03
park_sup					0.55	0.01
park_sup (log transformation with constant)	1.09	0.01	1.07	0.01		
Built Environment						
b_umn_t30jobs						
b_umn_t30jobs (log transformation)	-0.04	0.01				
Socioeconomic Context						
ct_sze_own (log transformation with constant)					0.08	0.09
ct_vehp_0			-0.40	0.01	-0.37	0.01

Notes: [a] Building, parking, and built environment features; AIC = -124.65, R^2 = 0.75.
[b] Building, parking, built environment, and socioeconomic context features; AIC = -124.92, R^2 = 0.75.
[c] Model 3 specification with additional transformed variables; AIC = -120.23, R^2 = 0.75.