

## **Perfect Fit Parking Initiative *Phase II* report Technical Appendix**

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The Metropolitan Area Planning Council's Perfect Fit Parking initiative has included two phases of research and data collection. Phase 1, which took place from 2015-2017, focused on collecting data from multifamily properties in 5 municipalities north of Boston: Arlington, Chelsea, Everett, Malden, and Melrose. Phase 2 (2017-2019) expanded data collection efforts to an additional 10 municipalities across the Inner Core. This memo summarizes the methodology for property selection, property manager surveying, overnight parking data collection, and statistical model development.

### **Property Selection**

#### *Phase I*

To select properties in Chelsea, Everett, Malden, and Melrose, MAPC worked with the planning department and city assessor in each municipality to identify multifamily residential developments that would qualify for the parking study. For Phase 1, this include multifamily developments that have 9 or more housing units. After manually filtering through the resulting developments with each municipality, MAPC was left with 396 properties to be surveyed across the four communities. A large number of the properties were lacking contact information for property management, so the sample size was reduced to 265.

For property selection in Arlington, which was added to the study area at the Town's request, municipal staff selected the nine multifamily residential properties eligible for the parking analysis. Developments were selected based on size, location and ownership type. Properties ranged in size from 24 to 176 units, and the types of developments varied, including subsidized and luxury, rental and condominium, and old and new developments. Across the five municipalities, a total of 274 properties were contacted to participate in the next steps of the data collection process.

#### *Phase II*

The goal of the second phase of data collection and analysis was to collect parking data from a larger and more representative geographic area. MAPC defined the Inner Core subregion as the study area, given the mix of the communities' transit accessibility and walkability. This is also the subregion seeing most of the multifamily development in the MAPC region. Unlike Phase 1, Phase 2 data collection restricted property surveys to more recent multifamily developments in an effort to get a more up to date picture of parking supply.

To ensure the properties surveyed were reasonably demonstrative of current development patterns in the region, MAPC utilized MassBuilds ([www.massbuilds.com](http://www.massbuilds.com)), the agency's collaborative inventory of past, present and future real estate development projects. From this database, MAPC pulled information about all multifamily developments of nine units or more, located in the Inner Core and constructed in 2000 or later. This collection of approximately 415 developments was used to construct a sampling frame intended to ensure that surveyed properties were representative of recent development. The inventory of projects from Massbuilds was characterized and separated into quartiles for nine different variables: number of units, median rent (tract), median income (tract), average block size, transit accessibility to employment, WalkScore, land use intensity (population + employment, tract), land use mix (population as a share of total intensity, tract), and average vehicle ownership (tract.) During the survey phase (described below), these statistics were calculated for each completed survey site and compared to the sampling frame. Where certain quartiles were underrepresented in the sample data, MAPC made special efforts to reach

out to developers and managers of residential properties that would help to achieve a more representative sample.

MAPC worked with city and town staff to obtain the relevant contact information for these properties. If that was not available, staff contacts also provided MAPC with multifamily assessor data. To supplement the information provided by the cities and towns, MAPC also contacted large property management companies and developers directly in an effort to collect multiple surveys from single points of contact. Community development corporations with residential portfolios in the Inner Core were also contacted to participate. Combining all of these sources, MAPC obtained a list of approximately 540 multifamily properties across the study area.

### **Property Manager Surveys**

#### *Phase I*

After the properties were selected, the property manager or owner of each development was contacted to complete an in-depth two-page survey regarding parking at their development. Questions detailed the type and number of housing units at each development, as well as the type and number of parking spaces available to residents. The survey asked further questions about parking, including whether there is a waitlist for parking, how residents can obtain additional parking beyond what is provided, if needed, and if there is anyone aside from residents that utilize parking on-site. A total of 126 surveys were completed for Phase 1 (a response rate of 46%). A copy of the survey is available in Appendix D.

#### *Phase II*

Only minor adjustments were made to the survey for Phase 2—a question about transportation services provided to residents was added, and respondents were asked to provide information about average rent among a range of options, rather than provide the specific rent cost. Of the 540 properties in the initial sample size for Phase 2, MAPC received completed surveys for 245 sites, indicating a response rate of about 45%. Despite communicating study parameters, some surveys for sites constructed prior to 2000 were received. When filtering out sites constructed prior to 2000 (36), the sample size was further reduced to 209.

### **Overnight Parking Data Collection**

#### *Phase I*

Following the completion of the surveys, MAPC staff assessed peak residential parking utilization by conducting overnight (12:00 AM- 4:00 AM) parking observations to confirm the number of parking spaces and to count the number of parked vehicles at each of the sites. Of the 126 surveyed properties, 22 properties did not provide off-street parking and 24 properties were inaccessible for overnight counts. Issues of accessibility were largely related to the lack of availability of on-site staff who could grant access to secured lots. Therefore, MAPC was able to successfully obtain occupancy information and retrieve data from 80 of the 126 properties visited overnight. Counts took place overnight on a weeknight in an effort to survey properties when it was residential parking usage rates would be at their peak. Counts in Chelsea took place in July 2015, and counts in Everett, Malden, Melrose, occurred in December 2015 and January 2016.

#### *Phase II*

MAPC employed the same methodology for performing the overnight counts for Phase 2, with counts taking place over several weekday nights in October, November, and December 2018 from approximately 11:00 PM-3:00 AM). Of the 209 surveyed Phase 2 sites constructed in 2000 or later, 24 did not have on-site parking available. Of the remaining 185 sites, MAPC was able to perform overnight

parking counts at 104 sites; as with Phase 1, garage accessibility presented a challenge. This presented an especially significant barrier for Phase 2, as two-thirds of the surveyed sites had at least some garaged parking. Fortunately, MAPC was able to obtain information about the number of parking spaces rented at 13 sites where parking is unbundled (residents pay separately from rent), and this information was able to supplement the overnight count data collected.

## 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 designated residential 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
<i>Building Features</i>	
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
avg_bedrms	Average count of bedrooms in housing unit of multifamily complex
rent_proom	Average monthly cost (US \$) of housing unit in multifamily complex per bedroom
rent_punit	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_rent	Tenure of housing units in multifamily complex (0=owner-occupied, 1=renter-occupied)
<i>Parking Features</i>	
park_bike	Presence of indoor bicycle parking at multifamily complex
park_cost	Average monthly cost (US \$) of first parking space at multifamily complex
cost_v_brm	Ratio of monthly parking cost of first parking space to monthly cost per bedroom
cost_v_unt	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
sfc_vs_gar	Ratio of garage parking spaces to lot parking spaces
eff_sup	Count of vehicle parking spaces per count of occupied housing units
<i>Built Environment</i>	
jobs_30min	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
<i>Socioeconomic Context</i>	

ct_inc_med	Median annual income for households in US Census tract
ct_size_own	Average household size of owner-occupied housing units in US Census tract
ct_size_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 radial 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.

Variable	n	mean	stdev	min	max	park_dem <sup>a</sup>		util_rate <sup>b</sup>	
						beta	p	beta	p
<i>Parking Outcomes</i>									
park_dem	189	0.73	0.34	0.02	1.73				
util_rate	189	0.72	0.17	0.09	1.00				
<i>Building Features</i>									
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							
avg_bedrms	189	1.61	0.41	1.00	2.80	0.15	0.03		
rent_proom	142	1,279.33	584.65	357.14	3,000.00				
rent_punit	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_rent	189	0.87	0.33	0.00	1.00	-0.22	0.00		
<i>Parking Features</i>									
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		
cost_v_brm	142	0.03	0.05	0.00	0.19				
cost_v_unt	142	0.02	0.04	0.00	0.14	-0.15	0.07		
park_garp	189	0.32	0.44	0.00	1.00				
sfc_vs_gar	189	41.24	100.27	0.00	482.00				
eff_sup	189	1.04	0.46	0.12	2.39	0.85	0.00		
<i>Built Environment</i>									
jobs_30min	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_craill	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		
<i>Socioeconomic Context</i>									
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).

Variable	Model 1 <sup>a</sup>		Model 2 <sup>b</sup>		Model 3 <sup>c</sup>	
	b	p	b	p	b	p
intercept	0.18	0.01	0.20	0.01	0.25	0.01
<i>Building and Parking Features</i>						
bldg_affp	-0.13	0.01	-0.08	0.03	-0.08	0.03
rent_punit (x 1,000)	-0.04	0.07				
park_sup	0.65	0.01	0.57	0.01	0.55	0.01
<i>Built Environment</i>						
jobs_30min (x 100,000)			-0.03	0.01		
<i>Socioeconomic Context</i>						
ct_vehp_0					-0.41	0.01

Notes: <sup>a</sup> Building and parking features; AIC = -108.23, R<sup>2</sup> = 0.78.

<sup>b</sup> Building, parking, and built environment features; AIC = -117.54, R<sup>2</sup> = 0.74.

<sup>c</sup> Building, parking, built environment, and socioeconomic context features; AIC = -119.38, R<sup>2</sup> = 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).

Variable	Model 4 <sup>a</sup>		Model 5 <sup>b</sup>		Model 6 <sup>c</sup>	
	b	p	b	p	b	p
intercept	0.48	0.01	0.13	0.01	0.18	0.01
<i>Building and Parking Features</i>						
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		
<i>Built Environment</i>						
jobs_30min						
jobs_30min (log transformation)	-0.04	0.01				
<i>Socioeconomic Context</i>						
ct_size_own (log transformation with constant)					0.08	0.09
ct_vehp_0			-0.40	0.01	-0.37	0.01

Notes: <sup>a</sup> Building, parking, and built environment features; AIC = -124.65, R<sup>2</sup> = 0.75.

<sup>b</sup> Building, parking, built environment, and socioeconomic context features; AIC = -124.92, R<sup>2</sup> = 0.75.

<sup>c</sup> Model 3 specification with additional transformed variables; AIC = -120.23, R<sup>2</sup> = 0.75.

After reviewing these models, MAPC selected Model 2 as the most robust predictor of parking demand, given the relatively low AIC and high R<sup>2</sup> value.