Factors Affecting Residential Parking Occupancy in Madison, Wisconsin

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Policy makers in urban areas throughout the United States are interested in managing parking provision and minimizing the negative impacts of excess parking, yet those policy makers often lack an understanding of how much the existing parking is used and how different factors affect its use. This paper presents a study of multifamily residential parking use and related factors at 80 sites in Madison, Wisconsin. Twenty-two factors, including neighborhood and building characteristics, are considered. During the evening peak, parking use ranges from 0 to 1.4 spaces per residential unit, and the existing supply is 67% occupied. This paper presents three simple models of parking occupancy that require only two neighborhood characteristics and three building characteristics. These models explain roughly two-thirds of the variation in occupancy. Neighborhood characteristics are highly collinear and explain roughly 40% of the variation. Building characteristics explain more than 50% of the variation. This work validates similar findings from prior studies of larger cities and also offers important guidance for practitioners in other cities to understand factors affecting parking demand and to develop models of their own. Given the vast amount of unused parking observed in this study, this work reinforces the notion that cities should implement policies to manage their supply better.

Policy makers in urban areas throughout the United States are interested in managing parking provision and minimizing the negative impacts of excess parking, yet they often lack a full understanding of how much the existing parking is used and how different factors affect its use. This paper presents a study of multifamily residential parking occupancy and related factors at 80 sites in Madison, Wisconsin. Twenty-two factors were considered, including neighborhood and building characteristics. This work resulted in three simple models of parking occupancy—each of which includes five variables that explain roughly two-thirds of the variation in occupancy—and offers important guidance for similar work in other cities.

BACKGROUND

For decades, the preeminent approach to parking policy has been to set minimum parking requirements in zoning codes. This practice became ubiquitous in the two decades from roughly 1950 to 1970, during which the share of cities that included parking requirements in their zoning codes grew from 20% to 95%. These minimum parking requirements have generally increased over time (*1*).

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This approach has the advantage of ensuring that each new building or development provides enough on-site parking to meet some reasonable share of peak demand and preventing spillover parking onto nearby streets and parking lots. However, it also has many negative consequences, including increased construction costs, which contribute to higher rents and lower densities; lower land values and tax revenues; increased automobile ownership and use; and environmental impacts (*2–6*).

Partly because of its link to automobile ownership, household travel choices, and housing affordability, residential parking is a common focus of research and policy (*7–11*). Throughout Madison, Wisconsin, new residential development often elicits concerns about how best to meet any additional parking demand. In central Madison, where bus service and bicycle accommodations are fairly robust and land values are high, decisions about parking provision are not trivial.

One key reason that developers and municipalities are often reluctant to scale back parking supply, however, is a lack of understanding of how much parking is used and uncertainty about how much is needed. As a result, parking is regularly oversupplied (*9, 11–13*). One study of 31 sites near transit in Portland, Oregon, and San Francisco, California, found that the average parking supply is 1.57 spaces per residential unit and occupancy is 1.15 spaces per unit, which translates to 73% (*14*). Another study of 41 sites in Chicago, Illinois, found that average supply is 0.61 spaces per unit and occupancy is 0.34 spaces per unit, or 56% (*11*).

An analysis of 27 mixed-use centers found that parking is 65% occupied on average during peak periods (*13*). The authors of that study found that even in locations with perceived shortages, parking is oversupplied by 45% on average and noted that "levels of parking provision are unmoored from demand, travel behavior, pricing, or other dimensions where theory suggests that there would be a relationship" (*13,* p. 182).

To establish more empirically driven parking policies and provision, practitioners need reliable estimates of parking demand for a wide range of conditions and contexts. Sufficient guidance does not exist, despite a longstanding focus on parking demand in research and policy.

The Eno Foundation, ITE, the Urban Land Institute, and other professional organizations have produced estimates of parking demand since at least as early as 1952, but these estimates do not sufficiently account for many key factors (*15*). ITE's *Parking Generation,* which provided data for 106 land uses, including residential, is the most comprehensive and commonly used resource available (*16*). However, its estimates are highly generalized and approximately half of the land uses, including several residential ones, contain only four data samples or fewer.

The Urban Land Institute's *Shared Parking* compiled parking demand estimates from various sources and offered guidance in providing shared parking facilities for mixed-use areas (*17*). Like

ITE's *Parking Generation,* however, it did not account for factors such as building characteristics, development density, transit service, or other transportation options.

Recognizing the limitations of the aforementioned resources, several studies related residential parking occupancy to many specific building and land use characteristics. The first comprehensive study took place in the Seattle, Washington, metropolitan area (*10, 12*). In 2012, researchers developed an extensive data set for 223 multifamily residential sites, including counts of parking occupancy between midnight and 5:00 a.m. Tuesday through Thursday. Using data from 208 sites, including seven explanatory variables, their model explained 81% of the variation in occupancy. That research led to the development of the King County Multi-Family Residential Parking Calculator, available online (*18*).

In a similar study of Washington, D.C., researchers collected data for 115 sites from 2014 to 2015 (*9*). Using data from 92 sites, including 11 explanatory variables, their model explained 84% of the variation in occupancy. That research also led to the development of an online parking calculator called Park Right DC (*19*).

Both studies—Seattle and Washington, D.C.—considered neighborhood characteristics such as density and transit access and building characteristics such as unit size, rent, and parking price. They also revealed that parking was regularly oversupplied. The average supply in Seattle was 1.3 spaces per unit, and the average use was 0.9 per occupied unit, which translates to 69% occupancy (*12*). In Washington, D.C., 60% of parking spaces were occupied (*9*).

Although those earlier studies led to the development of exhaustive data sets and robust models for occupancy in Seattle and Washington, D.C., their broad findings for general practice are limited. The current study resulted in a similar model for use in Madison—a considerably smaller city without rail transit—but it also provided insight that may be useful for other small cities interested in developing similar tools requiring the least amount of data. In doing so, this study focused on several of the simplest, most-intuitive models that minimized collinearity among the variables and required fewer data inputs but also explained parking use reasonably well.

METHODS AND DATA

This study considered a variety of data sources and several model variations. Two subsets of data were considered: (*a*) building and site characteristics and (*b*) location-specific neighborhood characteristics, including accessibility measures. These data sources are described below.

Site Selection

A first phase of sites was identified by using online searches and local directories, with the goal of achieving well-distributed geographic coverage throughout the city that represented a range of location-specific characteristics such as density, transit service, walking environment, and distance to jobs and other, nonwork destinations.

Because of a low response rate from property managers at these sites, however, a second phase of sites was chosen by identifying property owners that provided sufficient information for multiple buildings online, which minimized reliance on surveys. Although the highest concentrations of apartments were in central, transit-rich areas, special effort was made to identify sites in peripheral suburban areas. Because of a lack of comprehensive survey data, some variables of interest such as demographic characteristics of the residents and the prevalence of affordable housing were excluded from the study.

Parking Supply and Occupancy

Parking supply and occupancy were determined during field visits. Sites where parking was visible from the street or accessible to visitors were included. In some cases, tenants or property managers provided access to limited-access areas such as parking garages. Other restricted access sites were excluded from the study.

Members of the research team conducted field visits during peak periods, Monday through Thursday between 7:00 and 11:00 p.m., as reported by Smith (*17*). This approach differed from that of prior studies in which the peak period was defined as midnight to early morning (*9–11, 14*). However, this period was more likely to capture additional demand from evening visitors, eased data collection, and allowed for a larger sample to be collected.

For each site, field visits were conducted on two dates between July 2015 and June 2016, and the maximum observed occupancy was reported. Only off-street parking was included in these counts, but the availability of on-street parking was taken into account by using an indicator variable.

Site and Building Characteristics

To determine the number of residential units, unit size, number of bedrooms, rent, and parking price at each building, a series of data sources were considered in subsequent order until all the necessary data were obtained: (*a*) assessor records, (*b*) property-specific web pages, and (*c*) individual correspondence with property owners and managers, including phone calls, e-mails, and online survey forms.

Neighborhood Characteristics

Population and Employment Data

Population data were obtained from the 2009–2013 American Community Survey 5-Year Summary provided by the U.S. Census Bureau at the tract level. Jobs data were obtained from the Longitudinal Employer–Household Dynamics Origin–Destination Employment Statistics at the block level and aggregated to census tracts. These data were used to calculate population density, proximity measures, and gravity-based accessibility measures described next.

Proximity and Gravity Measures

Conventional accessibility measures include proximity and gravity measures. Because of their common use and ease of calculation, these measures were all considered during model development. In addition to the population and jobs data described earlier, data about the location of bus stops and frequency of service were obtained in General Transit Feed Specification format (*20*). Straight-line distances from each site to active transit stops and block group centroids—the smallest geometry for which population and jobs data were available—were calculated by using geographic information systems. Gravity-based accessibility measures were defined as follows:

$$A_i = \sum_i \left(\frac{a_j}{d_{ij}^2} \right)$$

where

A_i = gravity-based accessibility from origin i,
a_j = attractiveness of destination j, and
d_{ij} = distance from origin i to destination j.

The "attractiveness" of a destination is defined as the number of residents or employees in a zone or the scheduled number of arrivals per day for transit stations.

Walk Score, Bike Score, and Transit Score

Measures of walking, biking, and transit access were obtained from the WalkScore.com website (*21*). Its walk score assigns points on the basis of the number of amenities accessible within a reasonable walking distance. Its bike score is calculated on the basis of the type of bicycle infrastructure in an area, road connectivity, hills, amenities, and the number of bicycle commuters. Its transit score is calculated from the distance to the nearest transit station and the type and frequency of transit service (*20*).

Accessibility Measures

The accessibility measures considered in this study are similar in concept to the walk score but customized to account for destination types (work and nonwork) and modes (walking, transit, and automobile). These measures were calculated by using Sugar Access software, provided by Citilabs, which incorporates network, travel speed, and points-of-interest data from the HERE website and General Transit Feed Specification data for transit routes and schedules. The following specifications were used:

- Access to jobs was calculated during the morning peak and nonwork access during the off peak, as defined in the Sugar Access platform.
- Nonwork access was calculated on the basis of targets and weights outlined in Table 1 by using a default decay function that valued destinations within 5 min at 100%, destinations within 10 min at 25%, destinations within 15 mi at 10%, and so on, up to 60 min.
- Jobs were decay-weighted in accordance with the curves in Figure 1, which were derived from commute travel time data in the American Community Survey through methods outlined by Iacono et al. (*22*) and Kuzmyak et al. (*23*).
- Walking speeds were assumed to be 2.8 mph on the basis of prior research (*24, 25*).

TABLE 1 Sample Weights and Scores Used in Sugar Access for Nonwork Access Scores

Destination Type	Target	Weight
Restaurants, coffee shops, bars, pubs, wineries, and nightlife	8	40
General retail, bookstores, and department stores	4	15
Grocery stores	2	15
Errands: banks, pharmacies, and hardware stores	3	10
Parks, recreational areas, campgrounds, and golf courses	2	10
Schools	2	5
Cultural attractions, entertainment, and museums	1	5

Although the software can also produce accessibility measures for bicycle users, these measures were not included in the study. Bicycle users are much more sensitive to factors like the type of facility and traffic volumes, which the software does not yet take into account. In addition, every site received the maximum score for nonwork access by automobile, so automobile scores were excluded from the analysis.

Data Summary

Of 140 sites originally under consideration, complete data were compiled for 80. The geographic distribution of those sites is shown in Figure 2, and a summary of the data are presented in Table 2.

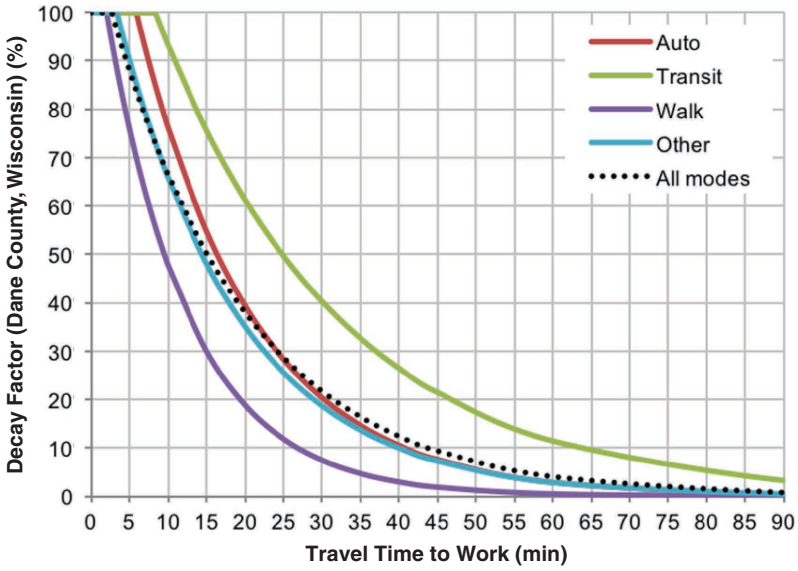

FIGURE 1 Decay functions for work trips by travel mode.

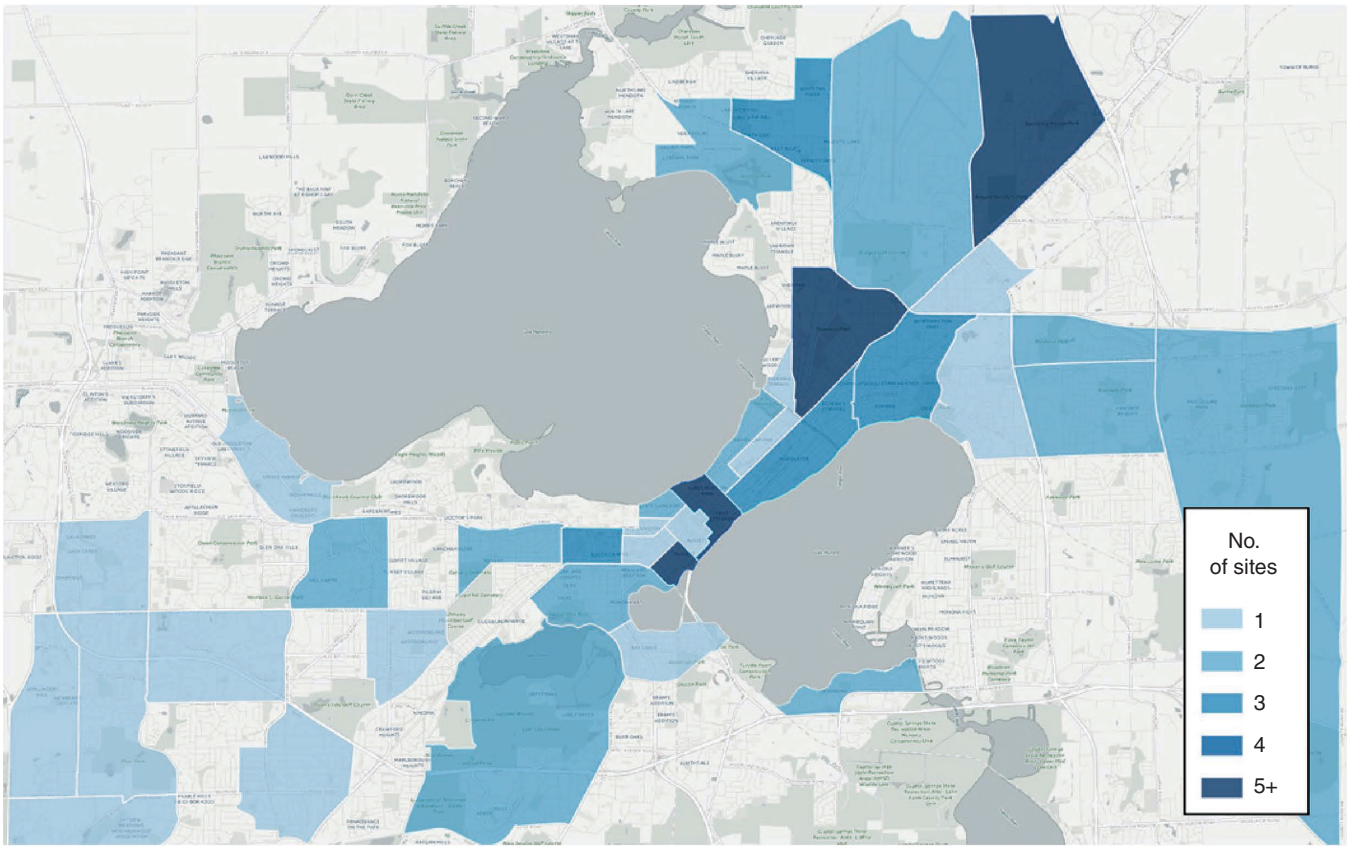

FIGURE 2 Distribution of 80 study sites throughout Madison.

TABLE 2 Data Summary and Descriptive Statistics for 80 Study Sites

Data Type	Variable Name	Description	Minimum	Maximum	Median	Mean
Parking supply–occupancy	pctOcc	Percent of available spaces occupied	39	100	67	67
	parkAvailPU	Available spaces per unit	0	2.33	1.09	1.13
	parkOccPU	Occupied parking spaces per occupied unit	0	1.41	0.76	0.74
Location measures	transitDist	Distance to nearest transit (km)	0.023	1.471	0.091	0.135
	transitGrav	Transit gravity (stops/km^2)	9,840	1,411,680	188,310	295,600
	popDens	Population per km^2	140	19,450	1,980	4,010
	jobsDens	Jobs per km^2	20	6,730	280	770
	actDens	Activities (residents + jobs) per km^2	340	23,850	2,080	4,780
	jobsGrav	Jobs gravity (jobs/km^2)	1,080	273,190	8,260	23,577
	actGrav	Activity gravity (activities/km^2)	13,510	4,648,200	57,010	245,180
Accessibility measures	accessWalk	Nonwork accessibility by walking	1	94	53	50
	accessTransit	Nonwork accessibility by transit	2	100	68	61
	accessAuto	Nonwork accessibility by automobile	100	100	100	100
	jobsWalk	Decay–weighted jobs accessible by walking	170	20,940	1,600	4,320
	jobsTransit	Decay–weighted jobs accessible by transit	30	61,950	27,730	28,270
	jobsAuto	Decay–weighted jobs accessible by automobile	83,780	157,080	133,110	130,010
Walk score	walkScore	Walk score	0	96	67	62
	transitScore	Transit score	10	63	49	46
	bikeScore	Bike score	31	100	94	85
Building specific	units	Number of residential units at site	3	404	39	65
	unitSize	Average unit size (ft^2)	230	1,310	710	700
	roomOccRate	Average number of bedrooms per occupied unit	1.00	3.40	1.30	1.46
	unitPrice	Average monthly rent per unit ($)	200	2,540	850	990
	parkPrice	Average monthly parking price ($)	0	185	0	44
	parkStreet	On-street parking available and in use (yes = 45; no = 35)				

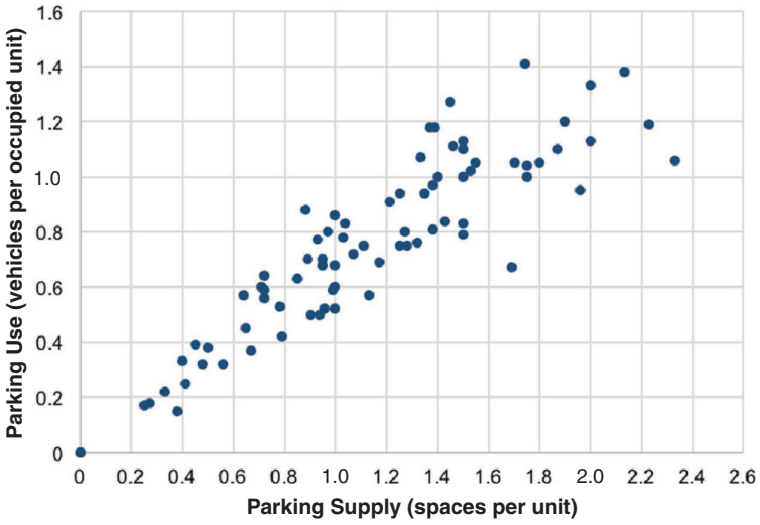

FIGURE 3 Relationship between parking supply and occupancy.

ANALYSIS

One key decision in model development is whether to include parking supply as an explanatory variable. Rogers et al. included parking supply in their model, but it was then the only significant variable (*9*). Rowe et al. excluded parking supply from their model, noting that they were interested in understanding parking demand in a way that could inform decisions about supply (*10*).

In fact, parking supply was more strongly associated to parking occupancy than any other explanatory variable in the data for Madison ($R^2 = .82$, as shown in Figure 3). While it improved the predictive power of the models substantially, it also made the effects of most other variables insignificant. To focus on the effects of neighborhood and building characteristics on demand, supply was presumed and excluded from all models in this study.

Ultimately, seven model variations were considered for estimating the number of parking spaces in use per occupied housing unit at each study site:

1. Conventional location measures as neighborhood characteristics,
2. Accessibility measures as neighborhood characteristics:
   – Accessibility measures developed in Sugar Access and
   – Walk score in lieu of accessibility measures,
3. Building-specific data, and
4. Best combination of neighborhood and building data:
   – Accessibility measures developed in Sugar Access,
   – Walk Score in lieu of accessibility measures, and
   – No accessibility measures.

For each of Models 1 through 3, the correlation coefficients and scatter plots among the dependent and independent variables were first examined to understand strength of associations, data distributions, and collinearity among independent variables. Gravity measures were transformed by taking the natural log of each. In contrast to past studies of factors affecting parking demand (*9, 10*), the current study deemed no other data transformations justifiable.

Package "leaps" in *R* was used to assess the incremental addition of variables in each model and to identify models that minimized the number of variables and the collinearity among variables while maximizing the explanatory power of the model (*26*). The results of these analyses are shown in Table 3. By using the same approach, variables from Models 1 through 3 were systematically evaluated for inclusion in Model 4, the results of which are shown in Table 4.

Analysis of the Model 1 variables, shown in Table 3, suggests that two variables were important to consider: transit gravity and population density. Neither activity gravity nor jobs gravity was significant when added to the model, and their sign (+) was unexpected, so only transit gravity and population density were considered moving forward.

TABLE 3 Results of Model Selection for Data Subsets, with First Four Variables Added

Number of Variables in Model	Model 1		Model 2a		Model 2b		Model 3	
	Variable Added	R^2	Variable Added	R^2	Variable Added	R^2	Variable Added	R^2
1	ln(transitGrav)	.32	accessWalk	.40	walkScore	.35	unitSize	.25
2	popDens	.42	jobsTransit	.41	bikeScore	.36	parkPrice	.52
3	ln(actGrav)	.43	accessTransit	.41	transitScore	.37	parkStreet	.56
4	ln(jobsGrav)	.43	jobsWalk	.41			roomOccRate	.56
Full model		.43		.41		.37		.56

TABLE 4 Results of Model Selection for Final Model, Combining Data Subsets, with First Six Variables Added

Number of Variables in Model	Model 4a		Model 4b		Model 4c	
	Variable Added	R^2	Variable Added	R^2	Variable Added	R^2
1	accessWalk	.40	walkScore	.36	ln(transitGrav)	.32
2	unitSize	.58	popDens, unitSize[a]	.53	popDens, unitSize[b]	.53
3	popDens	.63	walkScore	.60	parkPrice	.60
4	parkPrice	.65	parkPrice	.62	parkStreet	.62
5	unitPrice	.66	unitPrice	.63	ln(transitGrav)	.63
6	parkStreet	.66	parkStreet	.64	roomOccRate	.64
Full model		.66		.64		.65

[a]walkScore drops from two-variable model.
[b]transitGrav drops from six-variable model.

From the first submodel of Model 2, only walking access was considered, given the minimal contribution from additional measures. Similarly, only the walk score was considered from the second submodel of Model 2. Given the relative strength of Model 3, all site-specific variables were considered in Model 4.

On the basis of the results in Table 4, three models were considered for regression modeling. Each model incorporates two neighborhood characteristics, which vary from one model to the next, and three building-specific characteristics: unit size, parking price, and the presence of on-street parking. These three models are described in Table 5. Each model explains between 63% and 65% of the variation in parking occupancy, with accessibility measures helping to explain the most variation, followed by transit gravity, and then walk score. Estimates from the first submodel of Model 4 versus the observed parking occupancy are shown in Figure 4. For comparison, a full model including all the variables in the data set explained 75% of the variation in parking occupancy, but only three variables were statistically significant: population density, unit size, and unit price.

Table 5 also shows the standardized (beta) coefficient for each variable so as to illustrate the magnitude of effects from each variable. In each model, unit size had the largest effect, followed by walking accessibility in the first submodel of Model 4 and population density in the second and third submodels of Model 4.

DISCUSSION OF RESULTS

Residential parking occupancy ranged from 0 to 1.4 spaces per unit, and many factors helped to explain that variation. This study revealed that, while those factors are often highly correlated, isolating several variables and understanding their effects is important in estimating, satisfying, and managing parking demand.

Neighborhood Characteristics

Neighborhood characteristics explained about 40% of the variation in parking occupancy among the different buildings throughout this study. However, the considerable correlation between those variables generated many reasonable candidates for model inclusion. However, some variables performed marginally better than others and may have also been more intuitive or useful to practitioners.

TABLE 5 Final Regression Models

Variable	Unit	Model 4a		Model 4b		Model 4c	
		Coefficient	Beta	Coefficient	Beta	Coefficient	Beta
Intercept	na	0.583**		0.591**		1.063**	
popDens	Population per km^2	−1.72e-05**	−0.216	−1.99e-05**	−0.250	−2.16e-05**	−0.272
accessWalk	0 to 100	−3.56e-03**	−0.286				
walkScore	0 to 100			−2.56e-03*	−0.191		
ln(transitGrav)	Stops per km^2					−5.00e-02*	−0.164
unitSize	ft^2	7.05e-04**	0.468	7.09e-04**	0.471	6.95e-04**	0.462
parkPrice	$ per month	−1.14e-03**	−0.207	−1.35e-03**	−0.245	−1.42e-03**	−0.258
parkStreet	1 or 0	−5.78e-02	−0.086	−7.83e-02	−0.117	−9.22e-02*	−0.137
Multiple R^2		.65		.63		.63	

NOTE: Multiple R^2 for Model 4a is .65; for Model 4b, .63; and for Model 4c, .63; na = not applicable.
**Significant at 0.05; *significant at 0.01.

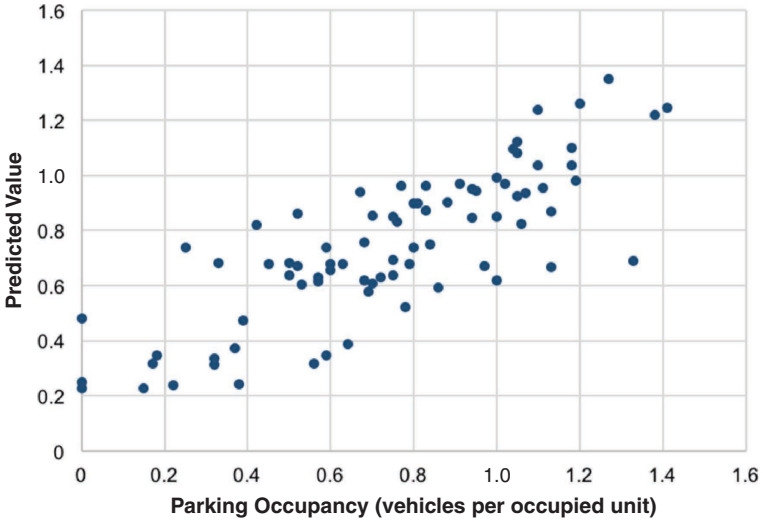

FIGURE 4 Parking occupancy versus predicted values from first submodel of Model 4.

Analysis suggested that two variables should be included in a final model: (*a*) population density and (*b*) some more comprehensive measure of accessibility, such as access to destinations by walking or transit gravity. Measures describing jobs gravity and activity gravity were problematic in the models tested.

A measure of walking accessibility developed by using the Sugar Access software was the single most useful measure of neighborhood effects in this study. However, only one variation of this measure, shown in Table 1, was tested. Therefore, an even more useful measure tailored specifically for this purpose may exist—for example, one that gives less weight to restaurants and bars but more weight to grocery stores, parks, schools. This direction for future research may be promising, along with other uses of accessibility measures. Walk score was useful in lieu of customized accessibility measures but much less useful in relation to customization or scenario planning.

Transit-related measures were useful only when no other accessibility measures were included. This result was unfortunate because it means that the models were not necessarily helpful in explaining how changes in transit service might affect parking demand. However, the negligible effects of transit might also be a consequence of the city's physical arrangement. For example, the number of sites with relatively high transit access to but relatively low walking access (or vice versa) may be insufficient. Future research should consider parsing these individual effects.

Building Characteristics

Building characteristics, while sometimes correlated with neighborhood characteristics, explained more than half the variation in parking occupancy—somewhat more than neighborhood characteristics did. In every model considered, the most important building characteristic was average unit size. For larger residential units, automobile ownership rates were higher, which likely reflected other related factors, such as the number of people living in those units, their incomes, or both. Other related variables, such as the average number of bedrooms per unit and unit price, provided little additional information.

The relationship between parking price and parking use was particularly important to consider for its potential application in transportation demand management, yet the nature of this relationship was complex. For example, households with no vehicles or low vehicle ownership rates were more likely to live in central locations with both better transportation options and a greater likelihood of a fee for parking. Conversely, buildings with parking fees may be less attractive to those with cars. Regardless of self-selection, however, this study pointed to an important effect of priced parking. While paid parking may discourage higher rates of vehicle ownership and use in general, it more likely helps to ensure that central locations will attract households with fewer vehicles and thereby limit parking demand, minimize traffic impacts in already-congested areas, and help to bolster walking, cycling, and transit use.

In thinking about the effects of parking price on parking use, practitioners should also consider other demand management strategies, such as subsidized transit passes, bicycle facilities, and access to ridesharing and carsharing services. Unfortunately, the available data and scope of this study precluded these factors from being tested.

In some model variations, the availability of on-street parking had some effect on off-street parking occupancy, but the effect could be quite small. Practitioners may wish to include this factor in parking occupancy estimates despite its small effect, simply to demonstrate that it is taken into account. In more peripheral areas, where on-street parking is less common, one may logically assume that it might not affect off-street parking use. In central areas, however, many older buildings have access to on-street parking, while newer buildings are denied access. The effect of this restriction, however small, may be of particular interest to practitioners.

Practical Applications

This study provided a better understanding of how parking is currently used at residential buildings in Madison. The application of this knowledge depends to some extent on the specific policy goals identified by the city or by other similar cities to which the findings might pertain. Those goals might include ensuring sufficient off-street

parking at all buildings, managing parking demand and bolstering multimodal transportation, increasing affordable housing options, or some combination of these and other considerations.

In any case, perhaps the most important finding from this study was that residential buildings provide more than 50% extra parking, on average. This excess parking exacerbates the aforementioned impacts, such as higher construction costs and added traffic.

Practitioners could put policies in place to reduce excess parking while ensuring that buildings provide the minimum amount of parking needed to satisfy demand. Weinberger and Karlin-Resnick defined sufficient supply as that which would leave 15% of spaces open or approximately 118% of parking occupancy, as reported in this study (*13*). This 118% rule might be a reasonable policy approach, but it ignores the complex, bidirectional relationship between parking supply and demand.

The strong association between parking supply and occupancy, described earlier, suggests that building owners and developers are somewhat conscious of the ways that parking demand varies but also that residents respond to parking supply in subtle ways, such as owning vehicles at lower rates and choosing to live in neighborhoods and buildings that best suit their lifestyles. By assuming that the latter effect is predominant, as prior research suggests, practitioners can manage vehicle demand and use by implementing policies that gradually nudge overall supply downward over time (*27–29*). In this case, policy makers may choose to cap parking supply at or near the levels identified in this study. This cap may be accomplished through maximum parking allotments in zoning codes, comprehensive travel demand management policies, or some form of tax or impact fee for parking.

In addition, practitioners must recognize that this study provided only a static view of parking use. Demand will likely evolve over time as the city's land use patterns and transportation options change, as individual values shift, and as the city attracts different types of residents.

CONCLUSIONS

This study examined peak period parking occupancy and related factors for 80 multifamily residential sites in Madison. It revealed that the existing supply of parking is only two-thirds occupied on average, which was fairly consistent throughout the city, regardless of other building characteristics. In a related finding, parking occupancy was closely related to supply. This result points to some interaction between the two but also suggests that outside factors affect both supply and demand in similar ways.

The location of a building and the specific neighborhood characteristics of that location had a significant relationship to parking occupancy, yet the effects of individual characteristics—for example, density, access to transit, and walking accessibility—were difficult to parse because they all tended to be very closely related. In this study, only two location measures, population density and some measure of accessibility, were needed to optimize model performance. Accessibility measures like those developed for this study are a promising focus for future research.

Building characteristics explained somewhat more variation in parking occupancy than neighborhood characteristics, but, again, these variables were closely related. Only two measures, unit size and parking price, were needed to optimize model performance, although the availability of on-street parking might also be included to inform policy decision making better.

This work resulted in a useful model of parking occupancy and validated similar findings from prior studies of larger cities; such validation suggests that these findings, collectively, may be somewhat transferable to other locations or useful in developing a more broadly applicable model of parking use. This possibility should be the subject of future work. This study also offered important guidance for practitioners in other cities to understand factors affecting parking demand and to develop models of their own through the use of limited data sources. Particularly, it described innovative data collection techniques as well as valuable new data sources and analysis tools, including accessibility measures.

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