Right Size Parking Project
King County Metro Transit

Technical Memo

February 7, 2013

Prepared by:
Center for Neighborhood Technology

TABLE OF CONTENTS

BACKGROUND

King County Metro was awarded a grant in the Federal Highway Administration (FHWA) Value Pricing Pilot Program. The project assembled local information on multi-family residential parking utilization to guide parking supply and management decisions in the future.

To prepare for the research effort, the project team assembled a methods committee of industry and academic experts. This committee provided valuable advice and feedback as the project team created three supporting documents to review literature and outline data collection and analysis methodology:

- **Literature Review** – Highlights previous studies that present standards for estimating parking demand and utilization in addition to studies that have inventoried multi-family parking.
- **Phase I** – Site selection and field data collection consisting of on-site parking utilization counts and assembly of physical building and pricing information.
- **Phase II** – Independent variable data collection, statistical analysis, and model development to predict parking utilization.

LITERATURE REVIEW

A literature review prefaced the methodology discussion of the research. Beginning with an overview of the present standards for estimating parking demand and utilization, the literature review found multiple studies which show that parking is often oversupplied. Many studies focused on the relationships between parking demand and various independent variables like household socio-demographic characteristics, housing type, qualities of the built environment, and parking price and supply. These variables are often considered for their potential influence on the imbalance between supply and demand for parking at multi-family residential properties. The literature review also documents past efforts to model these relationships as well as auto ownership models and their relationship to parking demand. Additionally, data sources that assess auto ownership or vehicle availability were reviewed for their potential to serve as proxy measures for estimating parking demand.

The full literature review can be found at: http://metro.kingcounty.gov/up/projects/right-size-parking/pdf/rsp-litreview_11-2011.pdf

PHASE I: SITE SELECTION AND FIELD DATA COLLECTION

The Phase I research methodology addressed the collection of parking data to help King County assess parking utilization in existing multi-family residential buildings to learn more about residents' parking needs. Approximately 240 properties were the subject of parking field counts assessing residential parking utilization. In addition, information about the physical building characteristics and parking/housing pricing was collected to support the Phase II research.

The full Phase I methodology can be found at: http://metro.kingcounty.gov/up/projects/right-size-parking/pdf/rsp-phase1-methods_12-02-2011.pdf

PHASE II: MODEL DEVELOPMENT

The Phase II research methodology addressed the statistical analyses and the development of a model predicting parking utilization at multi-family residential developments based on a set of independent variables tested in regression analysis. Independent variables tested capture the effects of housing characteristics, neighborhood household characteristics, accessibility, built form, and parking pricing and supply on parking utilization. The resulting predicted utilization is displayed on a website in which users have the ability to incorporate development-specific details to assess the resulting estimated parking utilization.

The original write up of the Phase II research design can be found at: http://metro.kingcounty.gov/up/projects/right-size-parking/pdf/rsp-phase2-methods_11-2011.pdf

RESEARCH OBJECTIVES

As discussed in the literature review, a lack of consensus exists on the factors that drive demand for parking utilization. While socio-demographic, housing, and built environment variables have all been shown to have an impact on parking and vehicle availability, their relative influence is a source of debate. There is more agreement on the fact that parking supply and pricing have a significant impact on parking demand and auto ownership, but these variables have been understudied. This research attempted to address and provide clarity on these issues in addition to providing practical tools to use in development and policy discussions. Specifically, the objectives of this research were to:

- Identify independent variables, both from a theoretical framework and a practical development and planning standpoint, to be tested in regression analysis of parking use data collected in Phase I
- Conduct statistical analysis to test independent variables' significance in predicting parking use
- Develop a model of parking use using regression analysis, maintaining the criteria that all variables be significant and multicollinearity be minimized
- Develop a website tool enabling interactive use of the model by interested stakeholders

PARKING UTILIZATION MODEL DEVELOPMENT METHODS

Information provided in this section summarizes methods, reiterates important points from the original methods documents, and indicates changes in methods that have occurred subsequent to the development of the research design. Please see full original methods documents at: http://metro.kingcounty.gov/up/projects/right-size-parking/.

SITE SELECTION

After initial feasibility testing of 20 sites, a total of 223 sites were assembled representing various types of multi-family development around urbanized King County. Convenience and quota sampling techniques were used to identify eligible sites. The geographic location of eligible properties was defined to ensure the sample was focused in areas where future multi-family residential development could potentially occur (as described in the Phase I research methods). Numerous developers, property owners, and property management companies were asked to participate in the data collection effort and then quotas were established to ensure a representative sample. Quotas were developed for the following independent variable characteristics: transit connectivity, employment access, average medium gross rent, and average median household income.

Dependent Variable

The dependent variable used in the model estimating parking utilization was 'observed vehicles per occupied residential unit' collected from the field data. Parking utilization was observed on Tuesdays – Thursdays between midnight and 5 AM for all residential parking identified by the property manager at each multi-family development. Parking was mostly provided in off-street garages or lots located on the multi-family parcel, but sometimes in dedicated on-street stalls or satellite garages. Each property manager was interviewed and asked to identify all available parking for residents, which was included in the study. Furthermore, sites selected for the study were screened for building age and available parking supply to control for potential undersupplied parking where spillover could occur. The end results was identification of sites where the predominant parking could be measured through parking counts, excluding sites where undefined off-site, on-street parking may have resulted in underrepresentation of parking use.

Independent Variables

As highlighted in the literature review, little consensus exists on the predominant drivers of parking utilization, although individual studies provide insight on variables to be tested and overall categories of variables to consider. The following theoretical framework was constructed to categorize potential independent variables and guide the regression analysis and model development process.

Parking Supply and Price:

As the two predominant indicators of demand, it is believed that parking supply and price will have a large impact on parking utilization. As basic theory suggests, low supply should correspond to low utilization and high prices should also indicate low utilization. Clearly, this can vary depending on context, but this basic trend was hypothesized to hold true in the data.

Property/Development Characteristics:

Studies have shown characteristics specific to the properties studied to be indicators of parking utilization. Higher density developments (both by lot size as well as by floor space) and lower rents have both correlated with low utilization rates in these studies, and therefore, were hypothesized to correlate in the data.

Neighborhood Household Characteristics:

Research has shown neighborhood income, household size, and commuters per household all correlating with auto ownership rates. Therefore, to the extent that neighborhood demographics reflect the building/development demographics, high income, large household size, and many commuters per household in the neighborhood are hypothesized to correlate with high auto ownership and thus high parking utilization rates.

Accessibility:

High levels of access to public transit, jobs, and services are all expected to correspond with low parking utilization rates. Conversely, poor access requiring high dependence on auto travel should correspond with high parking utilization in the data.

Built Form and Development Patterns:

Much research on auto ownership and auto use has highlighted the significance of built form and development patterns on auto dependence. High density, interconnected street networks, and a mix of land uses all have correlated with low auto ownership and use, and therefore, should theoretically correspond with low parking utilization in the data.

Because one variable can be represented in many different formats using different metrics, an extensive list of potential explanatory variables was analyzed. For example, while it was expected that transit access would correlate with parking utilization rates, the best measure of transit access to best explain utilization rates was unknown. Due to this, potential independent variables were grouped into the following five categories—parking supply and price, property/development characteristics, neighborhood household characteristics, accessibility, and built form and development patterns—enabling consideration of the greatest number of possible variables to capture these factors.

Data used to capture these variables were collected from a variety of sources. The field work surveys of property managers proved to be an important data source for the variables pertaining to specific buildings. The American Community Survey (ACS) 2006-2010 5-year estimates at the block group level and the 2010 Census at the block level were both used to capture characteristics of households in the neighborhoods as well as built environment characteristics (e.g. residential density). Local data were also obtained from the King County GIS Center (obtained in June, 2012), Walkscore (obtained April, 2012), Zipcar (obtained January, 2012), and Puget Sound Regional Council (PSRC) (employment data representing 2010). Local transit data compiled by CNT were also used, current as of May, 2012. Because data represent a snapshot in time, data were obtained with the effort to be as current and up-to-date as possible.

Because the dependent variable for the regression analysis pertains to the parcel level and data for these independent variables are at various geographic levels, data aggregation was necessary. Data pertaining to blocks or block groups were proportionally aggregated to a 0.5 mile buffer around each parcel. Many variables were aggregated using a gravity calculation (1/distance^2). These were point to point calculations (using Euclidian distances) from the centroid of each parcel to the point locations of the given data. Count and density calculations used a 0.5 mile buffer around each parcel and the land area contained within this buffer.

Attachment A lists all independent variables tested. The linear transformations tested (as described below in the regression analysis section), data sources, and aggregation methods are also noted in Attachment A.

REGRESSION ANALYSIS

MODELING PROCESS

Beginning with the presumption in regression analysis that the ordinary least squares (OLS) provides the optimal approach (with other methods only pursued if OLS proves inadequate), a simple linear regression model was used. However, because relationships between the dependent and independent variables were not all assumed to be linear, all variables were tested using various transformations. In other words, the correlations were tested for each independent variable in its linear form, but also in transformed forms, such as the natural log or inverse of each variable, to find the transformation that correlated best with the dependent variable. For variables that never equal zero (for example, however small, all parcels have some level of job access), the natural log, inverse, square root, square, and cube transformations were tested. Because the natural log and inverse cannot be calculated for a value of zero, for variables that could equal zero, only the square root, square, and cube transformations were tested. The dependent variable was then regressed against every independent variable (including all transformed versions) to test the individual correlations as a first step.

To construct the regression analysis, many approaches were tested to find the best method of including, removing, and finding the best set of variables. The linear regression function in SPSS was used, 'observed vehicles per occupied residential unit' was set as the dependent variable, and independent variables were included, added, and removed through various processes. Because each factor or characteristic was represented using many independent variables (as well as multiple transformations of each), multicollinearity, or a high level of correlation between independent variables, was an important consideration. High levels of multicollinearity can negatively impact the accuracy of models and must be minimized. In the end, the goal was to find the set of variables that made the most sense in terms of a theoretical framework and from practical development and planning standpoint, while also maintaining the criteria that all variables be significant (the probability that the coefficient is non-zero, or P less than 0.05) and all multicollinearity be low (as assessed through variance inflation factors, or VIF values, less than 5).

To build the model, many traditional statistical approaches were tested. A stepwise method was employed, using an entry criterion of 0.05 and a removal criterion of 0.10 for the probability of F, both within the five groups described above as well as ignoring the groupings. Another method involved adding independent variables to the regression one at a time, starting with the variables with the strongest correlation to the dependent variable. This approach was also applied to both the five groups of independent variables as well as to the full set of all variables. Another basic method tested was to include all variables in the initial regression and then remove variables one at a time, starting with those least significant.

While the R-square values resulting from each approach were good (in the range of 70 – 80%), none of the resulting sets of variables were ideal. Some approaches resulted in too many variables to be practical or useful in a planning or development context (well over 20). All approaches resulted with less than ideal or intuitive variables included. For example, one approach included the variable representing the count of three-bedroom units, but no other count or average number of bedrooms. From a planning or development standpoint, this does not represent a useful variable. Also, in all approaches, the resulting variables had high levels of multicollinearity.

To resolve these issues, the theoretical framework was revisited. Starting with a set of variables that appeared in the highly scoring results of multiple approaches and using the stepwise method, variables were tested based on logical candidates from a planning or development context. For example, in the case where the count of three-bedroom units was in the final set of variables, this was removed and all variables pertaining to average bedroom counts were added and tested in a stepwise method. Or, if two variables had high collinearity, such as block size and the transit connectivity index, one was removed and various variables were tested to replace the other.

Throughout this process, outlying cases were tested to ensure no one outlying property was influencing the fit too significantly. Cases (sample properties) with high leverage values (approximately > 0.5) or outlying residuals (as identified through separated tails in a residual histogram) were removed from the sample. In the end, 15 cases were removed based on these criteria, making the final sample 208 properties.

Supply of Parking

Supply is often cited as one of the most important variables in determining demand, and many past studies have found high correlations between the two factors. A high correlation was found in the data in this research as well, and the added explanatory power supply contributed in predicting parking use indicated that it should be included in the model. However, estimating parking utilization for the purposes of informing supply decisions should not be a function of supply. In other words, it was not desirable for the model to capture situations where parking utilization was low purely because little parking was supplied, rather than because little was demanded. Therefore, because the goal here was to estimate the full quantity of parking that would be demanded at a given property, parking supply was excluded as an independent variable from the model.

FINAL MODEL

The final model resulting from this regression analysis incorporated seven variables (listed and described below) – five pertaining to the property or development characteristics and two of the built environment, or specifically, access. The goodness of fit is explained with an R-square value of 81.0%, an adjusted R-square value of 80.3%, and a standard error of 0.16.

Table 1 below shows the seven variables, the transformation used, the coefficient values, the individual R-square values, and the stepwise R-square values. Individual R-square values represent the correlation between the given variable and the dependent variable. The stepwise R-square value represents the improving R-square value as each variable is added to the final model.

Table 1: Model Variables

Independent Variable	Transformation	Coefficient	Individual R Square	Stepwise R Square
Constant	NA	1.980910	NA	NA
Gravity measure of Transit Frequency	Natural log	-0.066639	55.5%	55.5%
Percent of Units Designated Affordable	Square root	-0.022966	27.6%	67.1%
Average Occupied Bedroom Count	Inverse	-0.360291	34.3%	73.7%
Gravity measure of Intensity (population + jobs)	Inverse	35,353.047567	53.3%	76.2%
Units per Residential Square Feet	Inverse	0.000139	17.1%	78.7%
Average Rent	Inverse	-154.420722	6.7%	80.0%
Parking Price as a fraction of Average Rent	Square root	-0.334655	18.1%	81.0%

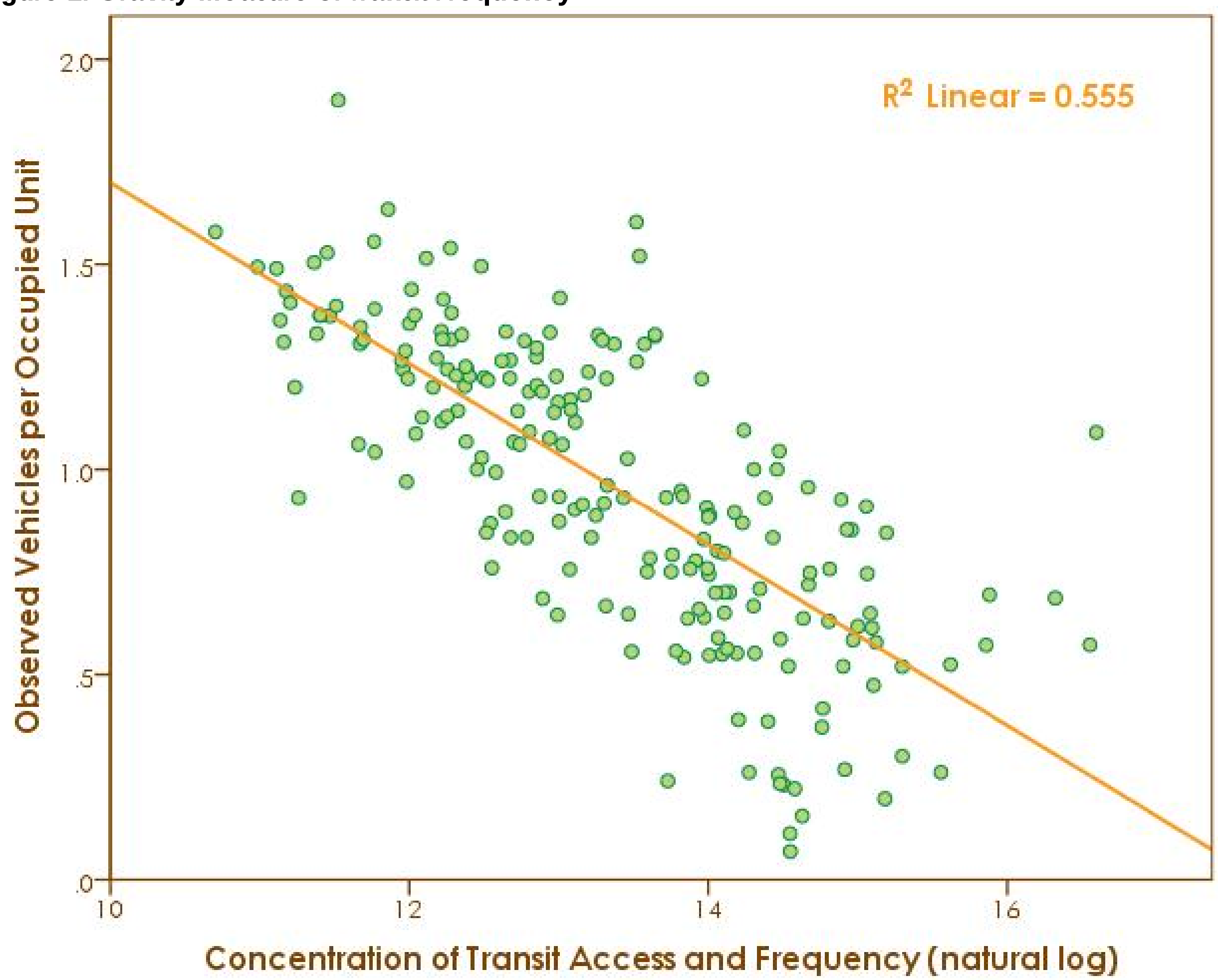
INDEPENDENT VARIABLES

Gravity measure of Transit Frequency

Gravity measures take into account both the quantity and proximity of the factor being measured by calculating the quantity divided by the distance squared from a given parcel's centroid. Therefore, the gravity measure of transit frequency accounts for all transit stops and stations, scaled by the frequency of service, and then sums the value to each parcel based on the distance from the given parcel. This can best be understood as a measure of concentration.

Many measures of transit access correlated strongly with parking utilization. Our data indicates, as seen in Figure 1, the natural log transformation of concentration of transit frequency and observed vehicles per occupied unit show a tight fit, and the R-square of 55.5% confirms this. Interestingly, transit access measures also correlated strongly with many other variables pertaining to the built environment (e.g. average block size). Therefore, the inclusion of a transit access measure in the model precluded the use of many other built environment or location characteristics, as multicollinearity would have been a problem. However, this was viewed as a positive finding, in the indication that transit is located and concentrated in areas where other built environment variables are high, and is able to account for many factors.

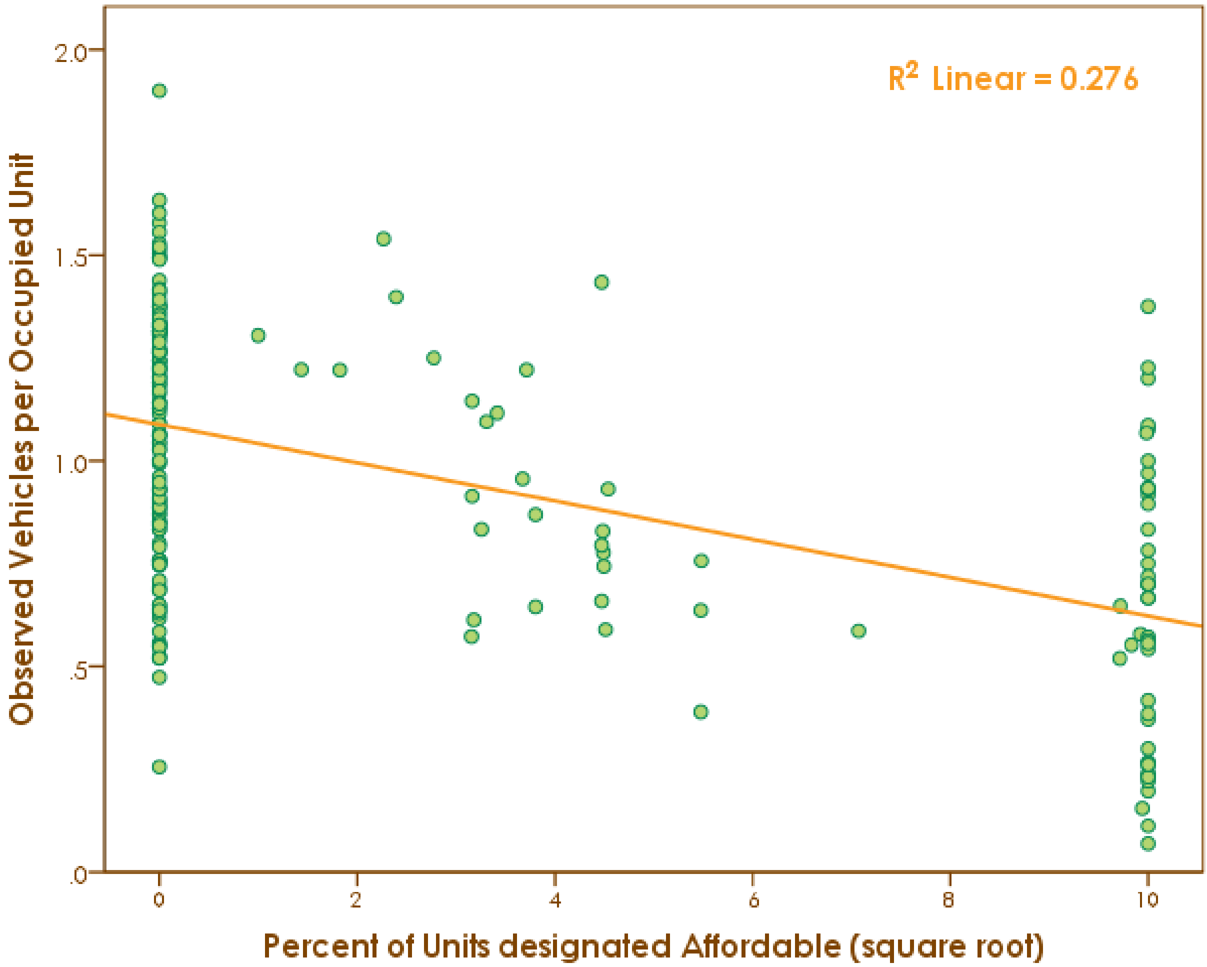
Figure 1: Gravity Measure of Transit Frequency



Percent of Units designated Affordable

This variable includes all units identified as affordable by any designation as a percent of all units (regardless of occupancy). Our data indicates that as the percent of affordable units goes up, parking utilization goes down (see Figure 2). In this case, the square root of the variable was the transformation that had the strongest correlation and was used in the final model. This was one trend that was frequently noted and agreed upon in the literature: affordable developments or those geared towards lower income households tend to demand less parking per unit.

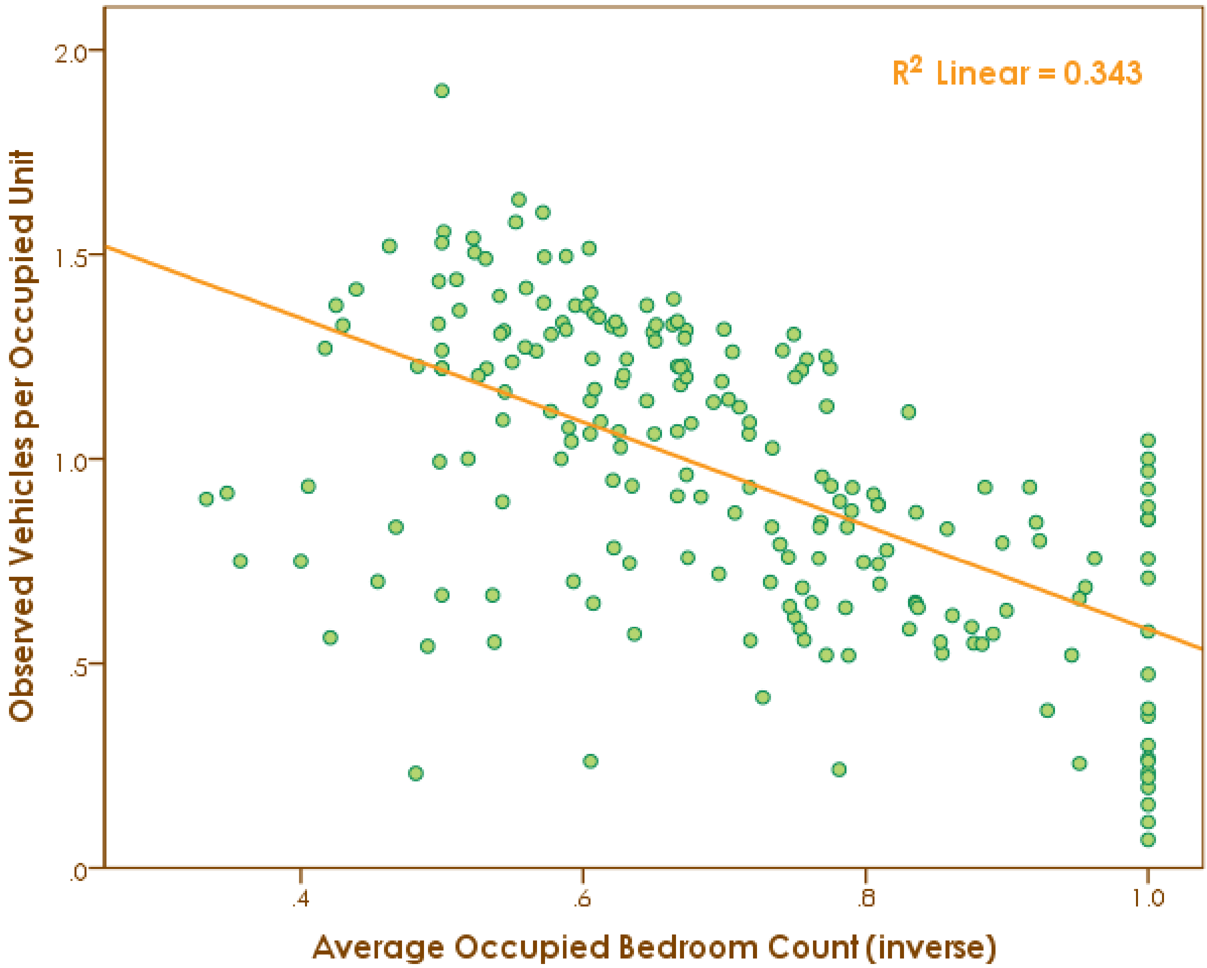
Figure 2: Percent of Units designated Affordable



Average Occupied Bedroom Count

Average occupied bedroom count is the average number of bedrooms in all occupied units. To calculate this average, studio units were assumed to have a bedroom count of one. Our data indicates that the average count of bedrooms has a positive correlation with parking utilization: as average bedroom count goes up, parking utilization goes up. However, because the inverse transformation had the strongest correlation, Figure 3 shows a negative trend.

Figure 3: Average Occupied Bedroom Count

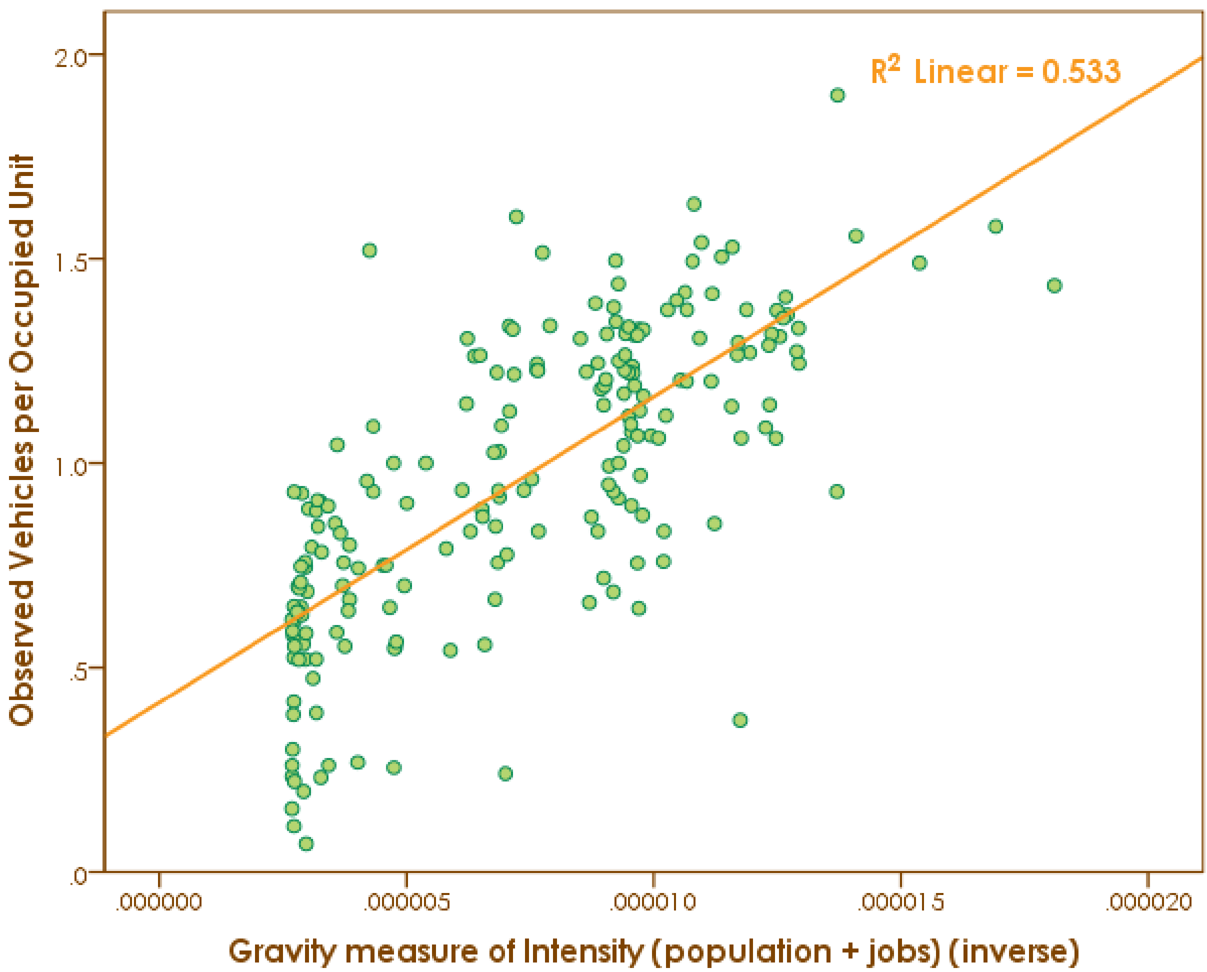


Gravity measure of Intensity (population + jobs)

As described above, gravity measures take into account both the quantity and proximity of the factor being measured by calculating the quantity divided by the distance squared from a given parcel's centroid. In the case of intensity, the factor being measured is the sum of population and jobs. Therefore, understanding this as a concentration, a high value can be the result of highly concentrated residential populations, highly concentrated jobs, or some combination of the two.

Previous research often found a strong correlation between both residential density and job access with auto ownership. The strong correlation of the gravity measure of intensity and observed vehicles per occupied unit observed in our data supports these findings. Measures of population concentrations, population and household density measures, and various measures of job access all correlated strongly with utilization: as people and/or jobs concentrate, parking utilization goes down. The inverse of the gravity measure of intensity was the variable that worked best in the model, therefore making the trend observed positive (as seen in Figure 4), or the opposite of that expected.

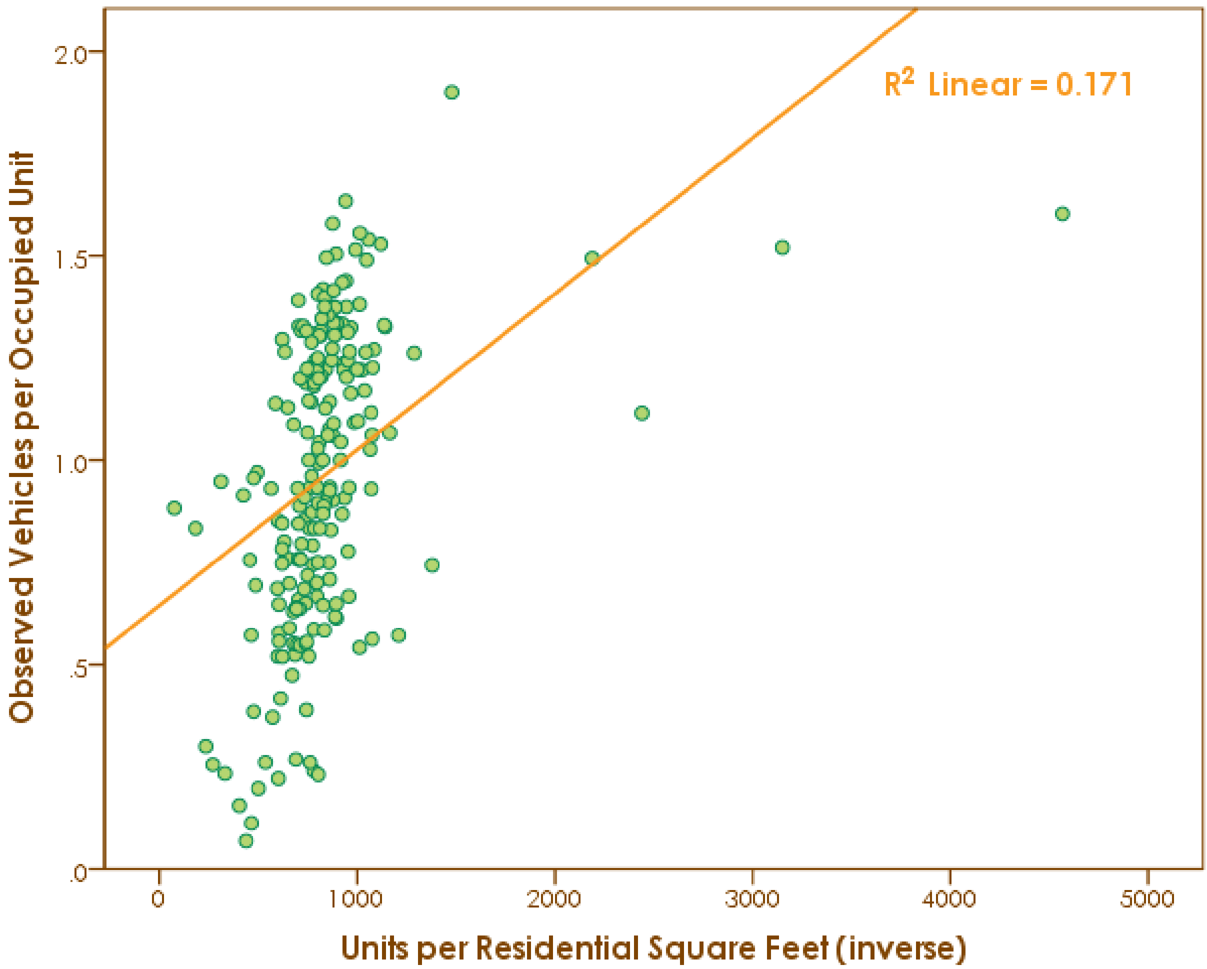
Figure 4: Gravity measure of Intensity



Units per Residential Square Feet

Obtained from the property managers, units per residential square feet is calculated as total residential units divided by the residential square feet of the development. This variable essentially captures the average size of units in that the greater the units per square feet, the smaller the units. Our data indicates that as units per residential square feet goes up, or average unit size goes down, parking utilization goes down. Again, because the inverse transformation showed the strongest correlation, it was used, and the opposite trend is observed in Figure 5.

Figure 5: Units per Residential Square Feet

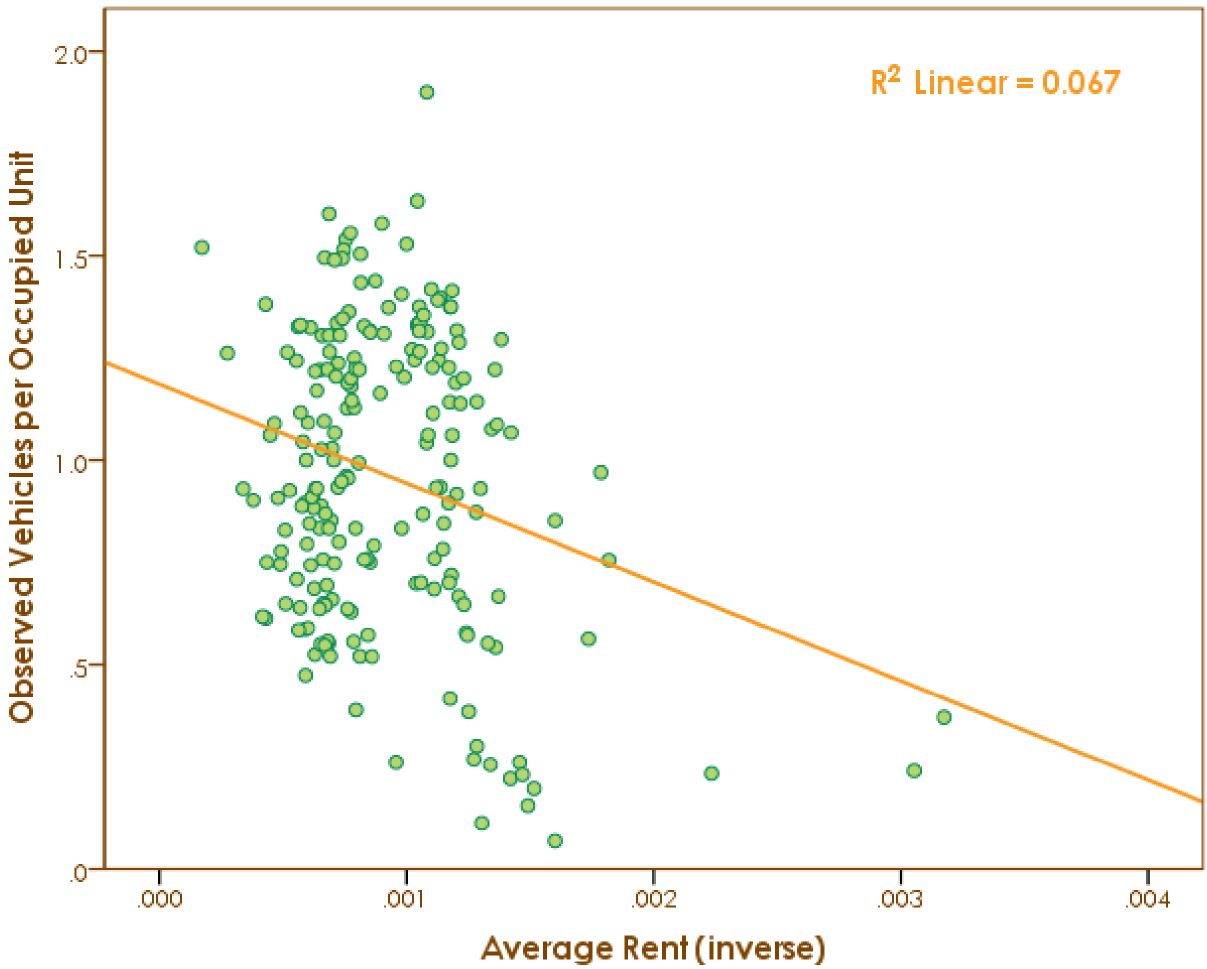


Average Rent

Obtained from the property managers, average rent represents the average monthly costs of all residential units in the building. Our data indicates that as average rent goes up, the observed parking utilization goes up. Because the inverse transformation was used due to its stronger correlation, the trend observed below, in Figure 6, is negative (as average rent goes up, the inverse of average rent goes down).

Average rent (in dollars) was not one of the variables with a very strong correlation by itself (R-square of 6.7%). However, when added to the set of variables comprising the model, average rent was significant and added more explanatory power than many variables with higher individual correlations.

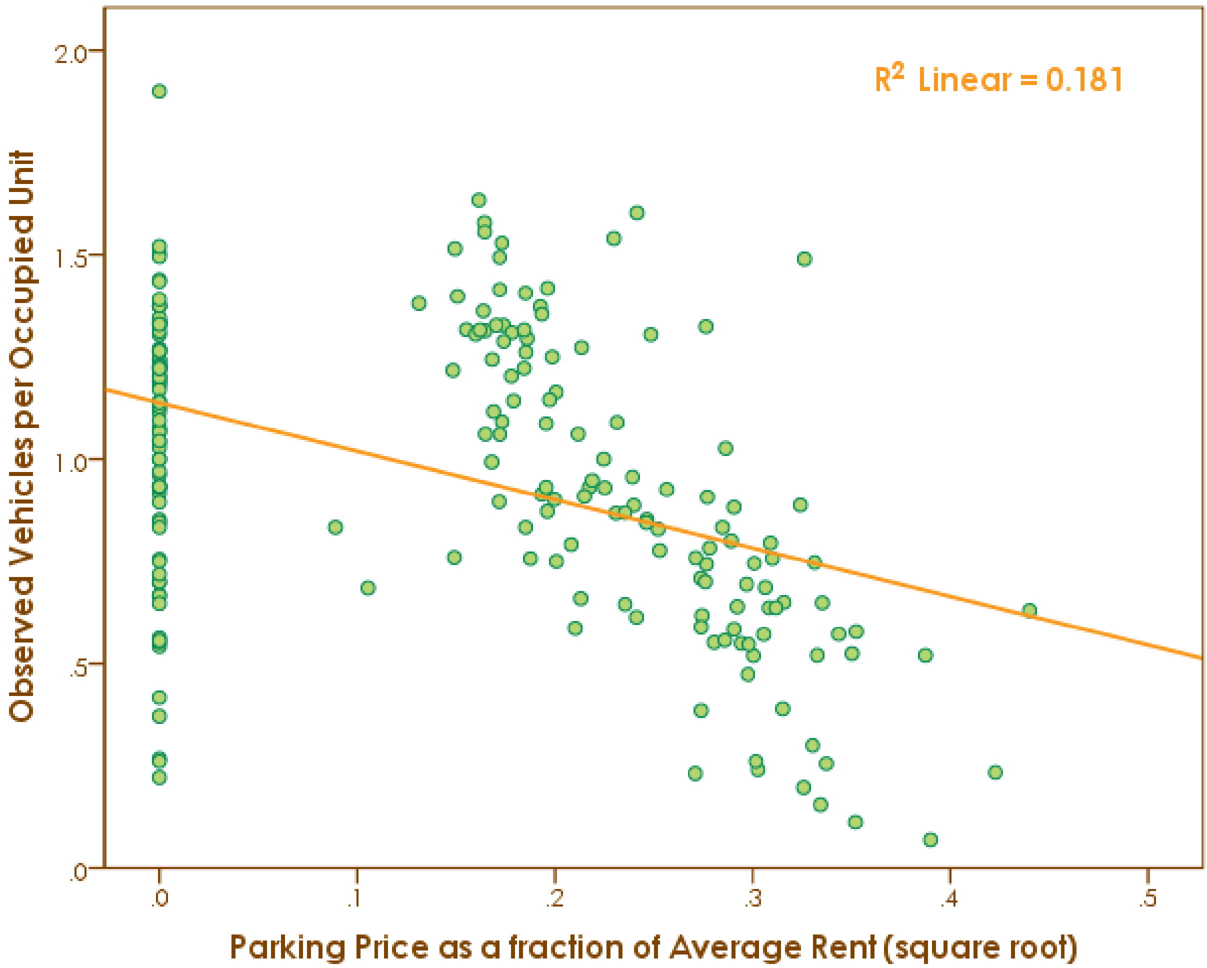
Figure 6: Average Rent (dollars)



Parking Price as a fraction of Average Rent

Parking price as a fraction of average rent is calculated as the monthly price of parking per stall divided by the average monthly rent. In properties with unpaid parking, this value is zero. This value approaches one as the cost of parking nears the cost of rent. According to basic economic theory and much literature, price should impact demand. However, parking price, as a dollar figure in and of itself, showed a very low correlation with parking utilization. A monthly parking price of $100, for example, is felt very differently between very expensive and very inexpensive residential developments. To account for this fact, parking price as a fraction of rent was used and correlated much more strongly with parking utilization. Our data indicates a negative trend, as seen in Figure 7, showing that as parking price nears the cost of rent, parking utilization goes down. Note that the square root transformation was used, as it correlated best with the dependent variable.

Figure 7: Parking Price as a fraction of Average Rent



LIMITATIONS

The final model resulting from this regression analysis can help support and guide decisions about parking supply and management. It cannot provide definitive answers about specific future policies or developments, but can serve as a resource to inform discussions as users weigh the factors affecting parking use and consider how much parking to provide.

MODEL ESTIMATES AND DATA COLLECTION

The final model is statistically very strong, but it is important to note that it is just a model and there is always error in estimates (the standard error for this model's estimates is 0.16; see Attachment B for the SPSS outputs of model parameters). Limitations on data collection also affect the model's accuracy. Observed parking mostly included supply that was on-site and off-street, unless additional parking provided for residents was noted by property managers. However, the sites selected for the study were screened based on building age and available parking supply, in order to control for potential undersupplied parking that could result in spillover. The result was sites studied whose predominant parking could be measured through parking counts, rather than those where undefined off-site parking would have resulted in an underrepresentation of parking use.

Additionally, data utilized in the model are collected and compiled representing one point in time. As factors of the built environment change (e.g. transit service is expanded), and parking utilization changes, it will be necessary to update both independent and dependent variables and reassess their relationships.

POTENTIAL DEVIATION FROM THE MODEL'S ESTIMATES

Real-world parking use can and will vary from these estimates for many reasons. Actions can be taken to reduce parking use below the levels predicted by this model. In addition to non-typical development opportunities, transportation demand management strategies, including the provision of residential transit passes, car sharing memberships, and bicycle facilities, have been shown to reduce car ownership and parking use. Some of these strategies were tested as the model was developed, but not enough cases were available to test with statistical rigor, so the model does not capture their influence.

MODEL COVERAGE

To ensure confidence in the model estimates, limits were established for the coverage area. The sample utilized for data collection covered a wide range of built environment characteristics and land uses, but it did not cover the full spectrum found throughout the county. Therefore, the coverage for which model estimates were calculated was limited to range of built environment characteristics found in the data collection sample. In other words, areas of the county that had lower transit service, population, or job concentrations than those found in the sample were removed from the coverage area.

RIGHT SIZE PARKING WEBSITE

The Right Size Parking Calculator (www.rightsizeparking.org) was developed to support and guide parking supply and management decisions. Using the final model developed to estimate parking utilization, resulting outputs for most developable parcels in King County are illustrated on this interactive, mapping website. Users have the ability to select a parcel, input details specific to a proposed development, adjust factors of the built environment, and see the new estimated parking utilization. Users can also, therefore, alter these characteristics and compare the impacts. For example, if the price for planned parking at a proposed building is reduced by half, the impacts on estimated utilization can be viewed. The website enables users to assess these impacts, helping to guide stakeholders' decisions regarding appropriate parking levels.

PROTOTYPICAL DEVELOPMENT

The five variables in the final model specific to the building and obtained from field work are not available for all parcels across the study area. However, value inputs for these variables are necessary to run the model and produce utilization estimates for any given parcel. To create estimates for each study area parcel, the model is run for a prototypical building, in which these five variables are calculated as the averages from the field work sample, and parking utilization is estimated for it. Because the results of this analysis are presented on the interactive Right Size Parking Calculator, the user has the ability to change any of these inputs and estimate parking utilization for any set of building characteristics.

It is not assumed that this prototypical building will exist on all parcels. It is simply used as a baseline to show how parking utilization varies across the region if building characteristics are held constant. It is expected that a user interested in an area would adjust the building characteristics to better match the local context, both at the parcel, neighborhood, or even city level. Each parcel is treated individually, and the model is run assuming this prototypical building is built on any given parcel (or set of merged parcels when this feature is used).

PARKING UTILIZATION IMPACT CALCULATIONS

Using best available research findings and accepted rule of thumb assumptions in the industry, additional impacts were estimated to highlight the additional 'costs' of parking for display on the Right Size Parking Calculator website. Impacts calculated include: total capital costs of parking, monthly costs per residential unit, GHG emissions from construction and maintenance, annual vehicle miles traveled of building residents, and GHG emissions from the vehicle use of residents. The calculations used for each impact are specified below.

TOTAL CAPITAL COSTS (LAND + CONSTRUCTION)[1]

Average capital costs per stall were calculated as land and construction costs for both surface and structure parking, which vary by land costs (see Table 2 below). To calculate land costs, parcels were assigned the average land value per acre of their associated suburban, urban, or central business district location, which were defined by locational, employment and residential density, and street network density (intersections per acre) characteristics.

MONTHLY COSTS PER RESIDENTIAL UNIT (INCLUDING OPERATIONS & MAINTENANCE)[2]

Average monthly operation and maintenance costs were calculated as a function of the parking ratio (stalls/unit) to estimate costs that would be potentially passed along to the residents on a per unit basis. These costs also vary by land costs, and were therefore calculated for suburban, urban, and central business district locations (as shown below in Table 2).

Table 2: Parking Costs by Land Use types

		Total Capital Costs (Land and Construction):		Monthly Costs per Residential Unit (including O&M):	
Suburban	Surface	*total stalls x*	$7,069	*parking ratio x*	$76
	Structured	*total stalls x*	$26,950	*parking ratio x*	$242
Urban	Surface	*total stalls x*	$23,269	*parking ratio x*	$177
	Structured	*total stalls x*	$31,583	*parking ratio x*	$275
CBD	Surface	*total stalls x*	$72,166	*parking ratio x*	$480
	Structured	*total stalls x*	$40,817	*parking ratio x*	$344

ANNUAL GHG EMISSIONS FROM CONSTRUCTION AND MAINTENANCE (KG CO_2E)[3]

Because emissions from construction and maintenance vary by the type of parking built, average estimates were calculated for both surface and structure parking.

kg CO2e from Surface Parking = total stalls * 71
kg CO2e from Structure Parking = total stalls * 173

ESTIMATED ANNUAL VMT OF BUILDING RESIDENTS[4]

Neighborhood level estimates of household vehicle miles traveled were averaged to a 0.5 mile buffer surrounding each parcel. It was then assumed that each parking stall built would contain an automobile that would be driven this average amount per year for the neighborhood.

---

[1] http://rightsizeparking.org/RSP_Parking_Rev_Cost_Memo.pdf
[2] Ibid
[3] http://iopscience.iop.org/1748-9326/5/3/034001/fulltext/; Scenario 2 was used as a conservative estimate
[4] Census block group level VMT was utilized from the Center for Neighborhood Technology's H+T® Index to derive VMT per auto: htaindex.cnt.org

Annual VMT of residents = total stalls * average VMT per auto

GHG Emissions from Vehicle Use of Residents (kg CO_2)[5]

Using the VMT estimates calculated above, greenhouse gas emissions were estimated using average fuel efficiency and emissions factors.

GHG emissions from residents' vehicle use = Total VMT / average MPG (21.6 miles/gallon[6]) * carbon emissions factor (8.78 kg/gallon[7])

CONCLUSIONS

The research found that characteristics of a building, and therefore, the residents that will be drawn to it, play a role in determining the parking utilization. Luxury three-bedroom units will draw residents with different parking needs than an inexpensive building consisting primarily of studio units. Similarly, buildings in different locations with different built environment characteristics will require different levels of parking. Residents of a building in a downtown location with high levels of transit access and job access will require less parking than a building in a suburban location with few amenities or travel mode options.

In the model development, no one aspect or type of variable told the whole story. When taking the final five building characteristics and running the regression analysis on those alone, an adjusted R-square value of 65.8% was obtained. Taking the two location characteristics and just using those alone estimated utilization with an adjusted R-square of 59.4%. In other words, considering a building or development outside of the context in which it is built, one cannot accurately estimate parking ratios. And conversely, the built environment alone cannot fully account for variation in parking ratios. To accurately estimate parking ratios or utilization, both the building itself and the location in which it is constructed must be taken into consideration.

The Right Size Parking project and Calculator website provide analysts, planners, developers, and community members with a new tool to weigh these factors and consider the proper provision of parking. By highlighting additional impacts of parking levels, the website also enables users to consider questions of parking from different angles and assess the implications of not appropriately sizing parking.

---

[5] Ibid
[6] http://www.fhwa.dot.gov/policyinformation/statistics/2010/vm1.cfm
[7] page 17 in http://www.theclimateregistry.org/downloads/2012/01/2012-Climate-Registry-Default-Emissions-Factors.pdf

Variable	Specific Variable	Transformations Tested	Data Source	Aggregation Method
Parking Supply and Price				
average cost per space per month	average monthly price ($) per residential space	square root, square, cube	field work	NA
	residential paid parking (yes/no)	n/a	field work	NA
	average parking price / average rent	square root, square, cube	field work	NA
car sharing access	carsharing spaces at development / total residential units	square root, square, cube	field work	NA
supply (on-site)	residential parking spaces / total residential units	natural log, inverse, square root, square, cube	field work	NA
	residential parking spaces / total residential bedroom count	natural log, inverse, square root, square, cube	field work	NA
Property / Development Characteristics				
average rent	average monthly rent ($) of all residential units	natural log, inverse, square root, square, cube	field work	NA
percent affordable units	percent of all residential units designated as affordable	square root, square, cube	field work	NA
	percent of all residential units designated affordable to 80-100% AMI households	square root, square, cube	field work	NA
	percent of all residential units designated affordable to 60-80% AMI households	square root, square, cube	field work	NA
	percent of all residential units designated affordable to less than 60% AMI households	square root, square, cube	field work	NA
percent senior designated units	percent of all residential units designated as senior units	square root, square, cube	field work	NA
dwelling units by land area (footprint density)	total residential units / land area of parcel	natural log, inverse, square root, square, cube	field work	NA
	total residential square feet / land area of parcel	natural log, inverse, square root, square, cube	field work	NA
	total building square feet / land area of parcel	natural log, inverse, square root, square, cube	field work	NA
building density	total residential units / total residential square feet	natural log, inverse, square root, square, cube	field work	NA
	total building square feet	natural log, inverse, square root, square, cube	field work	NA
	total residential square feet	natural log, inverse, square root, square, cube	field work	NA

total units (by type)	total residential units	natural log, inverse, square root, square, cube	field work	NA
	total occupied residential units	natural log, inverse, square root, square, cube	field work	NA
	total bedrooms (assuming studios equal 0)	square root, square, cube	field work	NA
	total bedrooms (assuming studios equal 1)	natural log, inverse, square root, square, cube	field work	NA
	count of occupied studio units	square root, square, cube	field work	NA
	count of occupied 1 bedroom units	square root, square, cube	field work	NA
	count of occupied 2 bedroom units	square root, square, cube	field work	NA
	count of occupied 3 bedroom units	square root, square, cube	field work	NA
	total bedrooms in occupied units (assuming studios equal 0)	square root, square, cube	field work	NA
	total bedrooms in occupied units (assuming studios equal 1)	natural log, inverse, square root, square, cube	field work	NA
	average bedrooms per unit (assuming studios equal 0)	square root, square, cube	field work	NA
	average bedrooms per unit (assuming studios equal 1)	natural log, inverse, square root, square, cube	field work	NA
	average bedrooms per occupied unit (assuming studios equal 0)	square root, square, cube	field work	NA
	average bedrooms per occupied unit (assuming studios equal 1)	natural log, inverse, square root, square, cube	field work	NA
Neighborhood Household Characteristics				
household income (median, average, and per capita)	average neighborhood income	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
	average median neighborhood income	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
	average per capita neighborhood income	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
average household size	average neighborhood household size	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
average commuters per household	average neighborhood commuters per household	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
presence of children (% population under 18)	average percent of neighborhood population under 18 years old	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
average age	average neighborhood population median age	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
average autos per household	average neighborhood autos available per household	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers

selected monthly owner costs and gross rent	average neighborhood gross rent	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
	average median neighborhood gross rent	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
	average neighborhood selected monthly owner costs	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
	average median neighborhood selected monthly owner costs	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
Tenure (renters v. owners)	average neighborhood percent renter households	natural log, inverse, square root, square, cube	ACS 2006-2010	averaged from block groups to parcel buffers
Accessibility				
access by land coverage scaled by frequency of service (CNT's TCI)	transit connectivity index	natural log, inverse, square root, square, cube	CNT's GTFS data	block group model applied to parcels
accessible area in a given time by transit (total area, jobs, etc)	accessible area (acres) by transit in 30 minutes	natural log, inverse, square root, square, cube	CNT's GTFS data	area accessible in 30 minutes by transit
	total jobs contained within a 30 minute transit access area	natural log, inverse, square root, square, cube	CNT's GTFS data and PSRC employment	count of jobs in transit access shed
	total service jobs contained within a 30 minute transit access area	natural log, inverse, square root, square, cube	CNT's GTFS data and PSRC employment	count of service jobs in transit access shed
	total population contained within a 30 minute transit access area	natural log, inverse, square root, square, cube	CNT's GTFS data and Census 2010	population in transit access shed
distance to nearest transit stop	network distance to nearest transit stop	square root, square, cube	CNT's GTFS data	NA
	Euclidean distance to nearest transit stop	natural log, inverse, square root, square, cube	CNT's GTFS data	NA
transit stop density	count of transit stops within 0.5 miles of parcel	natural log, inverse, square root, square, cube	CNT's GTFS data	count in parcel buffer
	density of transit stops within 0.5 miles of parcel	natural log, inverse, square root, square, cube	CNT's GTFS data	count in parcel buffer / land area (acres)
	gravity measure (quantity scaled by distance) of transit stops and frequency	natural log, inverse, square root, square, cube	CNT's GTFS data	gravity calculation from parcel centroid
job gravity	gravity measure (quantity scaled by distance) of total jobs	natural log, inverse, square root, square, cube	PSRC employment	gravity calculation from parcel centroid
job density	total jobs within 0.5 miles of parcel	natural log, inverse, square root, square, cube	PSRC employment	count in parcel buffer
	density of total jobs within 0.5 miles of parcel	natural log, inverse, square root, square, cube	PSRC employment	count in parcel buffer / land area (acres)
service job access (access to amenities)	gravity measure (quantity scaled by distance) of service jobs	natural log, inverse, square root, square, cube	PSRC employment	gravity calculation from parcel centroid
	service jobs within 0.5 miles of parcel	natural log, inverse, square root, square, cube	PSRC employment	count in parcel buffer
activity measure (residential + employment)	density of sum of population and jobs within 0.5 mils of parcel	natural log, inverse, square root, square, cube	PSRC employment and Census 2010	count in parcel buffer / land area (acres)
gravity activity measure (residential + employment)	gravity measure (quantity scaled by distance) of population plus jobs	natural log, inverse, square root, square, cube	PSRC employment and Census 2010	gravity calculation from parcel centroid

proximity to schools	gravity measure (quantity scaled by distance) of high schools	natural log, inverse, square root, square, cube	KC GIS	gravity calculation from parcel centroid
	network distance to nearest high school	square root, square, cube	KC GIS	NA
	Euclidean distance to nearest high school	natural log, inverse, square root, square, cube	KC GIS	NA
	total count of high schools within 0.5 miles of parcel	square root, square, cube	KC GIS	count in parcel buffer
	gravity measure (quantity scaled by distance) of middle schools	natural log, inverse, square root, square, cube	KC GIS	gravity calculation from parcel centroid
	network distance to nearest middle school	square root, square, cube	KC GIS	NA
	Euclidean distance to nearest middle school	natural log, inverse, square root, square, cube	KC GIS	NA
	total count of middle schools within 0.5 miles of parcel	square root, square, cube	KC GIS	count in parcel buffer
	gravity measure (quantity scaled by distance) of elementary schools	natural log, inverse, square root, square, cube	KC GIS	gravity calculation from parcel centroid
	network distance to nearest elementary school	square root, square, cube	KC GIS	NA
	Euclidean distance to nearest elementary school	natural log, inverse, square root, square, cube	KC GIS	NA
	total count of elementary schools within 0.5 miles of parcel	square root, square, cube	KC GIS	count in parcel buffer
	gravity measure (quantity scaled by distance) of all schools	natural log, inverse, square root, square, cube	KC GIS	gravity calculation from parcel centroid
	network distance to nearest school	square root, square, cube	KC GIS	NA
	Euclidean distance to nearest school	natural log, inverse, square root, square, cube	KC GIS	NA
	total count of schools within 0.5 miles of parcel	square root, square, cube	KC GIS	count in parcel buffer
walkscore	average walkscore within 0.5 miles of parcel	natural log, inverse, square root, square, cube	Walkscore	averaged from block to parcel buffers
	walkscore value of block containing parcel	natural log, inverse, square root, square, cube	Walkscore	NA
zipcar	gravity measure (quantity scaled by distance) of zipcar locations	natural log, inverse, square root, square, cube	Zipcar	gravity calculation from parcel centroid
	network distance to nearest zipcar location	square root, square, cube	Zipcar	NA
	Euclidean distance to nearest zipcar location	square root, square, cube	Zipcar	NA
	total count of zipcars within 0.5 miles of parcel	square root, square, cube	Zipcar	count in parcel buffer
	total count of zipcar locations within 0.5 miles of parcel	square root, square, cube	Zipcar	count in parcel buffer

Bike Access	total feet of bike routes (class 3) within 0.5 miles of parcel	square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	total feet of bike routes (all classes) within 0.5 miles of parcel	natural log, inverse, square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	total feet of bike routes (class 4) within 0.5 miles of parcel	square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	total feet of bike routes (class 2) within 0.5 miles of parcel	square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	total feet of bike routes (class 5) within 0.5 miles of parcel	square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	total feet of bike routes (class 0) within 0.5 miles of parcel	square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	total feet of bike routes (class 1) within 0.5 miles of parcel	square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
Built Form / Development Patterns				
entropy / land use mix measures / job mix measures	Herfindahl-Hirschman index using gravity percents of 8 job types	natural log, inverse, square root, square, cube	PSRC employment	gravity calculation from parcel centroid
	Herfindahl-Hirschman index using gravity percents of 3 job types	natural log, inverse, square root, square, cube	PSRC employment	gravity calculation from parcel centroid
	Herfindahl-Hirschman index using gravity percents of 6 job types	natural log, inverse, square root, square, cube	PSRC employment	gravity calculation from parcel centroid
	Herfindahl-Hirschman index using percents of 8 job types	natural log, inverse, square root, square, cube	PSRC employment	averaged from block groups to parcel buffers
	Herfindahl-Hirschman index using percents of 6 job types	natural log, inverse, square root, square, cube	PSRC employment	averaged from block groups to parcel buffers
	Herfindahl-Hirschman index using percents of 3 job types	natural log, inverse, square root, square, cube	PSRC employment	averaged from block groups to parcel buffers
residential density / gross density	residential household density	natural log, inverse, square root, square, cube	Census 2010	aggregated from blocks to the parcel buffer
	residential population density	natural log, inverse, square root, square, cube	Census 2010	aggregated from blocks to the parcel buffer
	total household density	natural log, inverse, square root, square, cube	Census 2010	aggregated from blocks to the parcel buffer
	total population density	natural log, inverse, square root, square, cube	Census 2010	aggregated from blocks to the parcel buffer
	gravity measure (quantity scaled by distance) of total population	natural log, inverse, square root, square, cube	Census 2010	gravity calculation from parcel centroid
average block size / intersection density / block density	average block size in acres	natural log, inverse, square root, square, cube	Census TIGER/Line	land area (in acres) / count of blocks in parcel buffer
	intersection density	natural log, inverse, square root, square, cube	Census TIGER/Line	count in parcel buffer / land area (acres)
	count of intersections within 0.5 miles of parcel	natural log, inverse, square root, square, cube	Census TIGER/Line	count in parcel buffer
pedestrian environment	feet length of car accessible roads within 0.5 miles of parcel	natural log, inverse, square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	feet length of pedestrian accessible ways within 0.5 miles of parcel	natural log, inverse, square root, square, cube	KC GIS	sum of length (ft) in parcel buffer
	density of feet length of car accessible roads within 0.5 miles of parcel	natural log, inverse, square root, square, cube	KC GIS	sum of length (ft) in parcel buffer / land area (acres)
	density of feet length of pedestrian accessible ways within 0.5 miles of parcel	natural log, inverse, square root, square, cube	KC GIS	sum of length (ft) in parcel buffer / land area (acres)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.900[a]	.810	.803	.1601834987

a. Predictors: (Constant), inv_grv_intensity, inv_avg_rent, inv_units_per_res_sqft, sqrt_park_price_per_rent, inv_avg_occ_bdrms_studio1, sqrt_pct_afford, ln_gravity_transit_frequency

b. Dependent Variable: obs_over_occ

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.857	7	3.122	121.692	.000[a]
	Residual	5.132	200	.026		
	Total	26.989	207			

a. Predictors: (Constant), inv_grv_intensity, inv_avg_rent, inv_units_per_res_sqft, sqrt_park_price_per_rent, inv_avg_occ_bdrms_studio1, sqrt_pct_afford, ln_gravity_transit_frequency

b. Dependent Variable: obs_over_occ

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.981	.254		7.803	.000		
	inv_avg_rent	-154.421	38.796	-.166	-3.980	.000	.550	1.819
	inv_units_per_res_sqft	.000	.000	.151	4.482	.000	.835	1.197
	sqrt_pct_afford	-.023	.004	-.259	-6.148	.000	.534	1.872
	inv_avg_occ_bdrms_studio1	-.360	.088	-.167	-4.073	.000	.569	1.759
	sqrt_park_price_per_rent	-.335	.105	-.120	-3.188	.002	.670	1.492
	ln_gravity_transit_frequency	-.067	.017	-.225	-3.888	.000	.284	3.523
	inv_grv_intensity	35353.048	6016.133	.345	5.876	.000	.276	3.626

a. Dependent Variable: obs_over_occ

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.080785654	1.597279429	.963375164	.3249472171	208
Std. Predicted Value	-2.716	1.951	.000	1.000	208
Standard Error of Predicted Value	.015	.113	.029	.011	208
Adjusted Predicted Value	.061698392	1.613297462	.963549829	.3249460289	208
Residual	-.3843965232	.3773984909	.0000000000	.1574517892	208
Std. Residual	-2.400	2.356	.000	.983	208
Stud. Residual	-2.416	2.367	-.001	1.001	208
Deleted Residual	-.3895747066	.3810002208	-.0001746643	.1632693758	208
Stud. Deleted Residual	-2.446	2.395	.000	1.005	208
Mahal. Distance	.884	102.845	6.966	9.003	208
Cook's Distance	.000	.063	.005	.007	208
Centered Leverage Value	.004	.497	.034	.043	208

a. Dependent Variable: obs_over_occ