A PRACTICAL METHOD FOR DEVELOPING CONTEXT-SENSITIVE

RESIDENTIAL PARKING STANDARDS

by

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ABSTRACT OF THE DISSERTATION

A Practical Method for Developing Context-Sensitive Residential Parking Standards

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Responsibility for establishing minimum parking requirements for new development largely falls on local governments. Unfortunately, many municipalities do not create parking standards that are appropriate to the various uses and locations that they regulate. Local parking standards are rarely derived from parking utilization studies, and are instead based on small, nationwide samples drawn from varying land use contexts offering varying transportation options. The standards applied to a particular development often do not depend on its physical environment.

The present research takes an important step in improving parking regulation: it develops a method for computing context-sensitive residential parking standards. First, it reviews transportation analysis literature to discern the latest thinking on the relationship between vehicle ownership—the main component of residential parking demand—and environmental and demographic variables. Second, it translates these lessons into a form appropriate for land use regulation. Third, it proposes and validates a method for estimating household vehicle ownership using only regulation-appropriate variables.

The proposed method, called the VULO method, for Vehicles from Unit choice with a Location-based Offset, is a useful tool for evaluating current residential parking standards and developing new standards. It is based in the latest understanding of the relationships between residential unit choice and vehicle ownership. It is procedurally simple: use microdata to estimate household vehicle ownership, and correct that estimate to align the estimated and actual average vehicle ownership at the Census block group level. It is designed to use only publicly available data, allowing planners throughout the US to implement it immediately. Finally, it offers better estimates of household vehicle ownership than alternative methods.

The VULO method offers the promise of rationalizing residential parking standards throughout the US. If implemented, it could reduce residential parking oversupply, especially in infill situations. In turn, this should result in accelerated infill development, less expensive housing, and more pleasant urban environments. At a minimum, it will advance the discussion of whether and how to improve parking standards.

Acknowledgement

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My deepest gratitude goes to my wife and son. Herself an academic, Amy counseled and supported me through a sometimes arduous process. Jonah, for his part, patiently waited his whole life for me to finish. Thanks and love to you both.

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Chapter 1. Introduction and summary

Off-street parking standards specify the number of parking spaces required by a municipality for a particular residential development. They are designed to ensure that new development does not impose undue costs on the general public: spillover parking[1] and traffic congestion due to the use of on-street parking (Willson, 1995; 2000). These parking standards affect parking supplies directly and indirectly: They influence the developer proposing a new project to a planning board, and they influence the planning board in evaluating the application. Also, a developer's lender usually wants to see plenty of parking in a project it finances, to ensure its viability (EPA, 1999:2; Schwanke, 2003:79; Stein Engineering, 1997:17), and local standards can be gauges of parking adequacy. Parking standards hold substantial power to guide residential development.

The main goal of this research is to create a scientifically sound, practical method for forecasting household vehicle ownership to help in setting appropriate parking standards. The method is intended to be immediately and broadly usable throughout the U.S. This chapter sketches the relationship between this research and the use and impacts of parking standards in the U.S. It concludes with a preview of the dissertation.

A brief history of U.S. parking standards

When automobiles first came into existence, curb parking was easy and free. Only the wealthy owned cars, and parked them at the curb in spaces also used for tethering horses (Kay, 2001). As automobiles multiplied however, free parking became

[1]This is the situation wherein residents or patrons park in a way that places unwanted demand on shared on-street parking or in private lots.

harder to find. Drivers cruised the streets looking for vacant spots, wasting time and creating congestion. The solution was to institute parking requirements as part of zoning.

The first off-street parking standard was promulgated in 1923, in Columbus, Ohio (Shoup, 2005: 607). Los Angeles was the first major city to follow suit, in 1935 (Ferguson, 2004). However, the predominance of minimum parking standards appeared just after World War II. Of 76 cities surveyed in 1946, 17 percent had standards; by 1951, 71 percent of these cities had or were adopting them (Shoup, 2005:22). Oakland, California, was among the late adopters, setting minimum parking standards for apartments in 1961 (Bertha, 1964).

Beginning in the 1960s, state and local governments have worked to reduce excess development standards, such as roads that were too wide. Some trace this movement to the failure of urban renewal projects, growing environmental awareness, and later, the oil embargo in the early 1970s (Kay, 2001). The continued study of off-street parking standards and utilization is a part of that movement. Ferguson (2004) cites seven reviews of parking standards published between 1964 and 1972.

The 1990s spawned a new perspective on parking and planning in general. The well-regimented development engendered by old-fashioned zoning codes is decried as sprawl and damned by modern-day planners and scholars for its aesthetic, social, economic and health consequences. The responses come in movements spanning architecture and planning, carrying various names—new urbanism, neotraditionalism, smart growth, and others. The responses share a common thread. They all involve reducing our collective dependence on automobiles.

Accordingly, parking standards are among the zoning elements under attack. The American Planning Association recently published *The High Cost of Free Parking*, the culmination of an planning professor's quest, begun in 1978, to debunk the idea that free parking is everywhere essential to business and prosperity. The author, Donald Shoup, argues that the current practice of setting minimum parking standards subsidizes automobile use and contributes to sprawl (Shoup, 2005).

Improving versus abolishing parking standards

Why not abolish residential parking standards, then? Why conduct research to refine them rather than to advocate for their elimination? As a step toward eliminating standards, Shoup (2005) and Litman (2006) argue for unbundling the cost of residential parking—allowing residents to lease as many parking spaces as they choose for a fee separate from their rent. This would allow existing parking spaces to be rationed by increasing prices, much as increasing parking meter fees in a commercial business district reduces street parking utilization rates or subsidizing commuting by transit decreases automobile commuting.

The main difference is in the time scale of the decisions in question. For retail parking, a change in parking rates can almost immediately influence a shopper's choice about where to park or, with more lead time, what travel mode to use to reach the store. For employee parking, carpools or other alternate arrangements can be established over the course of days or weeks. Residential parking demand, however, is driven by vehicle ownership. Cars are expensive, and vehicle ownership habits are difficult to change. The market for residential parking has relatively high barriers to entry and exit, which make it a less theoretically perfect market than the markets for other parking, with the practical implication of making rationing by price difficult.

While unbundled parking can be a goal to strive for, it is not the only response. It confronts significant practical challenges, as regulators will be slow to absolutely eliminate parking standards—a radical change in practice. Consider the example of shared parking, the idea that land uses with different parking demand time profiles can share parking lots. Instead of each use having a dedicated lot sized to accommodate the projected peak parking demand, shared lots can be sized for the maximum aggregate demand of the uses, which is less than the sum of the peaks. (See Figure 1.1 for an illustration[2].) The practice was formally established and endorsed by the Urban Land Institute in their 1983 publication, *Shared Parking.* However, reviews of parking planning more than ten and twenty years later revealed that parking was rarely shared in practice (Institute of Transportation Engineers, 1995; M. S. Smith, 2005).

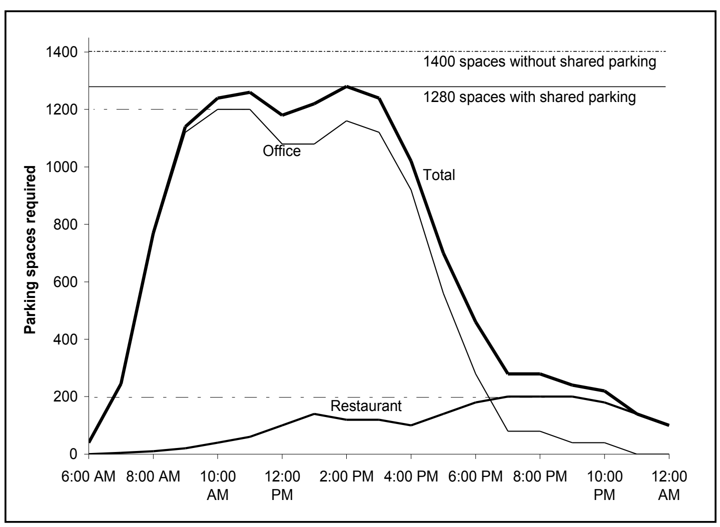

Figure 1.1. Shared parking analysis: Parking requirements

[2]Parking requirements for a restaurant with 10,000 sq. ft gross leasable area and an office building with 400,000 sq. ft gross leasable area (by the author, using default data from ULI, 1983:86, for a weekday in June).

One of unbundled parking's proponents, Todd Litman (2006), calls for more accurate parking standards as a step preceding unbundled parking. This is a more evolutionary approach, as contrasted to the elimination of residential parking standards or implementation of parking maximums, which is happening in very few urban areas (Millard-Ball, 2002). Improved parking standards fit into the current development regulation process, and therefore hold the promise of making incremental yet important improvements in the near term.

Uncertainty and excess in parking standards

Problems with parking standards arise when they lead to too much or too little parking. Unfortunately, planners are generally unsophisticated in setting parking requirements. Despite parking researchers' agreement that an array of local variables influence parking demand (ITE, 1995; CalTrans, 2002), planners tend to use "rules of thumb" to set standards (Willson, 1995). A survey of the planning departments of 138 southern California cities clarifies this finding (Willson, 2000). The most common source of information to set minimum parking standards was a survey of nearby cities' standards. National standards were used almost as often. Commissioning parking studies, the most promising approach for setting context-sensitive standards, scored only about one-tenth as important an approach as surveying nearby cities. Planners appear overwhelmingly likely to use parking standards that are not comprehensively related to the project being regulated.

Planners cope with the imprecision in parking standards by erring on the side of oversupply. Shoup (2005:81) reviews research showing that minimum parking requirements for office buildings often exceed the parking generation rates published by the Institute of Transportation Engineers (ITE), which are based on measurements of peak usage across the nation. Willson's (2000) survey of planners in southern California indicates that the planners are generally satisfied with their parking standards, while a sizeable minority express concern that they lead to parking undersupply. Less than 3% of respondents report concern about parking oversupply. Willson (2000) argues that planners are risk averse, and much more sensitive to the immediate costs of undersupply than to the more diffuse and delayed costs of oversupply, discussed below.

Willson (2000) also reviews research that indicates important negative effects of excessive nonresidential parking standards. For example, increasing the price of parking also increases transit use; given that oversupplying off-street parking makes pricing difficult, this suggests that oversupplying nonresidential parking increases auto use. Other research shows that minimum parking requirements often exceed measurements of peak parking demand and national standards. Willson argues that negative impacts from parking oversupply combined with generous parking standards lead to regional costs.

Shoup and Willson's work focuses on nonresidential parking standards, for the most part. Whereas excessive nonresidential parking standards may well encourage driving and disrupt the urban fabric, why are residential parking standards important? There are at least two good reasons to reduce excessive residential parking standards.

Impacts of excess parking supply

Bertha (1964) studied the implications of residential off-street parking requirements by examining apartment buildings built before and after the city of Oakland, California, first required off-street parking. In June of 1961, apartment buildings in one multifamily zone were required to provide one off-street parking spot for every dwelling unit, and those in another zone were required to provide 0.75 spaces per unit; before that, there was no such requirement. Bertha considered 45 buildings permitted between June 1957 and June 1961, which had no parking requirement, and 19 buildings permitted after the zoning change. He analyzes development density, costs and revenues, and draws a number of conclusions. After the zoning change, median development density fell and median number of units per development fell. In an effort to command higher unit prices to maintain profitability in the face of greater land costs, developers increased their unit sizes but were unable to pass all added development costs to the consumer, and profitability fell.

Two of Bertha's results stand out as particularly important. First, increasing parking supply decreases density. Where land prices dictate surface parking, the parking reduces the effective development density and therefore the number of activities within walking distance of other activities. Compounding the problem is the finding that people may be willing to walk less far through a parking lot than along a more pleasant streetscape (Parsons Brinckerhoff Quade and Douglas, 1996).

Table 1.1. Total cost estimates per parking stall (1997 US Dollars)

	Surface Lot	***Above-Ground Multi-Level Structure***	***Below Ground***
Land	$6,300	$750	$0
Construction	$2,750	$14,400	$28,000
Design, Contingency	$500	$3,400	$6,600
Interest Payments*	$8,400	$16,200	$30,250
Operating Costs*	$1,750	$4,200	$4,200
Total	$19,700	$38,950	$69,050

*The initial present value of a 24-year stream of costs.
Source: Adapted from Victoria Transport Policy Institute, 2006: Table 5.4-7

Second, increasing parking supply decreases profitability, or conversely, increases costs. Bertha (1964) found a loss in profitability as land costs were divided among a smaller number of units—a direct implication of decreasing density. Added parking entails other costs as well. See Table 1.1 for what may be conservative estimates of parking costs. For some projects in New Jersey at least, the costs for structured parking have doubled in the period from 1999 to 2005 (Goldsmith, 2007).

These added costs can have two effects: developers may be less willing to build and/or units may become more expensive. Where developers are unwilling to work, urban redevelopment stalls. Where the market will bear a high enough price to pay the added costs of parking, developers will build more expensive housing. Neither result is desirable.

Preview of the research

Researchers have proposed a range of responses to the problem of excessive nonresidential parking standards (Litman, 2006). Because nonresidential parking demand is driven by vehicle use decisions that may change from day to day, many of these approaches revolve around charging for parking. Residential parking is driven by household vehicle ownership, decisions about which are of a much longer time scale than the day. As a result, many of the solutions proposed to correct nonresidential parking excesses are not appropriate for residential developments.

This dissertation is designed to help correct existing residential parking standards. "Establishing more accurate standards" is third in a list of twenty-one innovations that the Victoria Transport Policy Institute recommends to reduce excess parking (Litman, 2006). That is the aim of this work.

The dissertation research begins, in Chapter 2, with a review of literature on projecting and explaining household vehicle availability[3]. The aim of the review is to discern the current knowledge of the household, demographic and locational factors that influence vehicle availability. This understanding is a prerequisite for developing a credible and reliable method for establishing residential parking standards, as residential parking demand is dominated by the demands due to household members' vehicles.

Chapter 2 includes summaries of predictive models used by Metropolitan Planning Organizations (MPOs) and explanatory models created by academics and other researchers. It includes a synthesis of the reviewed work, and presents a number of conclusions:

- Location within a land use and transportation landscape, characterized variously by development density, land use mix, and local and regional employment accessibility, is systematically associated with differences in household vehicle availability.
- Household sociodemographic characteristics, such as income and number of workers, have more substantial influence[4] on vehicle availability than do location-related variables.

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[3]In this dissertation, vehicle availability and vehicle ownership will be used interchangeably to mean the number of cars and trucks owned by, leased by, or otherwise available to household members, as in the case of company cars. Although "vehicle ownership" is perhaps more intuitive, "vehicle availability" is becoming the preferred term (Cambridge Systematics, 1997b).

[4]For the sake of readability, this dissertation uses terms like "influence" to mean degree of association between predictors and the dependent variable. Nothing in this work should be taken to imply causation. It includes no experiments or statistical methods designed to differentiate causation from association, nor does it attempt to evaluate others' analyses of causation.

There are spirited and important debates on the causality of any relationship between land use and travel behavior. However, for the purposes of this research I assume that the question of whether different land use causes different household vehicle ownership decisions can be ignored at the margins. An initial defense of this assumption is the fact that anyone projecting travel behavior of any sort currently makes the assumption that current relationships among key variables will persist for some time into the future. If anything, this should apply more to vehicle ownership, being a long-lived investment decision, than to more transient manifestations of travel decisions such as trip frequency or mode choice.

- There is as yet no consensus on whether housing location is endogenous to vehicle availability, nor on the best way to cope with any endogeneity that exists.

Chapter 3 draws on the understanding developed by the literature review to answer key operationalization questions. The studies reviewed in Chapter 2 all rely on data that is not available to planners who set or enforce parking standards. Demographic variables such as household income, number of workers in the household, and age are not determined by the sorts of land use characteristics that appear in parking standards. This raises the question of how to capture the effects of these demographic characteristics using only the land use variables that are available to typical parking regulators. Also, characteristics of the built environment such as job accessibility or development density must be calculated at some geographic scale. The studies in Chapter 2 assume environmental uniformity at scales ranging from the zip code area to the land parcel, partly because the aims of the studies differ. Because the choice of geographic scale does influence projections from the method, this raises the question of the appropriate geographic unit when the purpose is to establish residential parking standards.

Chapter 3 addresses in four steps the question of how to capture variation in household vehicle availability with regulation-appropriate variables. First, the chapter reviews existing residential parking standards; the results indicate that bedrooms, unit type and location are the three variables to use. They appear frequently in existing standards—suggesting that they can be used consistently by regulating boards—and they are physically linked to the housing unit. The conclusion is that these three variables are sufficient, in the sense that no other variables are appropriate for addition to the set.

Second, the chapter considers the variation in household vehicle availability in New Jersey along the dimensions of bedrooms, unit type and location. The distributions of average vehicle availability by bedrooms and unit type are summarized at the Census tract, with a population of 4,000 on average, and the Public Use Microdata Area (PUMA), with a minimum population of 100,000. The conclusion is that all three dimensions—bedrooms, unit type and location—capture substantial variation in vehicle availability; each of them is necessary.

Third, the chapter explores the relationship between the regulation-appropriate variables and some of the predictor variables used in studies in Chapter 2. Using ordinary least-squares regression[5] on households in north and central New Jersey, located by their PUMA, the chapter estimates the relationships between the regulation-appropriate variables—bedrooms, unit type and location—and demographic variables—household workers, nonworking adults, children and income—and household vehicle availability. The main conclusions are that bedrooms, unit type and location have expected relationships with demographic variables, for the most part, and that the three regulation-appropriate variables have significant influence on vehicle availability both directly and through their relationship with the demographic covariates. This section establishes the theoretical basis for using bedrooms, unit type and location in a parking standard.

Finally, Chapter 3 addresses the question of how we should characterize household location, given that our aim is to establish residential parking standards based

[5]The reviews in Chapter 2 suggest that ordinary least squares (OLS) is not the most appropriate regression technique for estimating household vehicle availability, in part because it takes on discrete values. OLS is used in the text to fit into the omitted variable bias analysis and for ease of exposition. Appendix A demonstrates that the conclusions drawn in the text, based on OLS, are also supported by a method appropriate to discrete dependent variables.

on household vehicle availability. The chapter reviews theoretical considerations surrounding the choice of geographic scale, and presents a quantitative study of the geographical scale of variation in household vehicle availability. Using data from the Census Transportation Planning Package (CTPP), the chapter conducts an F test to evaluate the accuracy benefit decreasing the geographic unit from the tract to the block group. The result of the test suggests that the block group is preferable to the tract.

Chapter 4 draws on the lessons of previous chapters to propose and evaluate a regulation-appropriate method for projecting household vehicle availability. Following a set of method design criteria based on the work of preceding chapters, the method, termed Vehicles from Unit choice with a Location-based Offset, is described and illustrated. The method's performance is evaluated analytically, through the derivation of an expression for its error field, and numerically.

Chapter 4 validates the method using a special tabulation of Census data purchased for that purpose. The data encompass 3,900 block groups across New Jersey, selected from among the 6,448 inhabited block groups because they have a sample size of 50 or more households. This set of 3,900 block groups includes a set of 729 tracts for which data for all constituent block groups are reported.

First, the data are used to answer more conclusively the question of whether block groups or tracts are preferable for establishing residential parking standards. As in Chapter 3, an F test is employed to determine whether the move from a smaller number of larger tracts to a larger number of smaller block groups is justified by improved fidelity. Unlike in Chapter 3, where the utility of areal averages for a single combination of household population and unit type are compared, the method here evaluates the use of all combinations of bedrooms and unit type. This analysis disconfirms that the block group is the preferable areal unit for the method proposed here.

Second, the data are used to evaluate the fidelity of the household vehicle estimation method. The method is exercised to project household vehicle availability for every unit type and bedroom combination for every block group in New Jersey, and compared to the data. The fidelity is evaluated by quantitatively comparing it to using PUMA-level regressions of vehicle availability on bedrooms and unit type. These analyses show that the method fits the data better than the alternatives.

Chapter 5 concludes by reviewing the dissertation and presenting recommendations for further research. In particular, two further tasks must be accomplished before the research presented here can be implemented. First, a method must be developed to account for projected household incomes. Developers of urban infill housing often aim their products at a higher price point than is typical for the block group. The omitted variable bias work in Chapter 3 points toward a way to cope with expected income aberrations, but a full method must be developed. Second, visitor parking must be estimated in a methodical way. This will be challenging and potentially labor intensive, as there is no widely measured proxy for visitor parking as there is for owner parking. Nonetheless, some measurements have been made. The measurements must be extrapolated in a theoretically grounded way. Chapter 5 discusses a stochastic model that may be a starting point for this work.

Even without these extensions, however, this dissertation research represents a significant step forward in conceptualizing residential parking demand and enabling more thoughtful residential parking regulations. The research demonstrates the possibility of more accurate parking standards. It provides methods necessary for benchmarking existing standards. Finally, it represents the vast majority of the work necessary to revise existing residential parking standards throughout the US.

Chapter 2. Vehicle availability in the transportation literature

Parking planners have only recently acknowledged the systematic relationship between a site's parking needs and its location. Nonetheless, other analysts have long been studying spatial variation in an excellent proxy for residential parking demand[6]. In general, parking demand can be decomposed into two parts: the demand created by vehicles owned by or otherwise available to regular users, and the demand created by occasional users. For retail, the episodic parking demand by shoppers overwhelms the regular demand of workers. For most office uses, regular workers fill far more parking spaces than do visitors. For housing, residents' parking demand dominates visitor demand. The parking demand due to residents is driven by "vehicle availability": automobiles owned, leased, or otherwise available to households.

How should existing vehicle availability patterns relate to residential parking standards for new development? This question has at least four parts. First, we need to know how the standards are going to be used. Traditionally, residential parking standards specify a minimum number of parking spaces that must be supplied off-street for a given residential development. Some municipalities use parking standards to establish maximum allowable parking supply, but this is very rare, and moreover much more common for commercial than for residential uses (Millard-Ball, 2002; City of Seattle, 2006; City of Portland, 2005). Also, some standards allow a fraction of required spaces to be supplied on-street or in shared lots (for example, see State of New Jersey, 1997). For the sake of discussion, we assume that the traditional use—minimum off-street

[6]Unless otherwise noted, the term "parking demand" is used to mean the peak number of parking spaces that users of a given facility would seek to fill, given prevailing prices. In most but not all cases, residential off-street parking is provided without the imposition of a use charge.

standards—will prevail, although the analyses in this dissertation apply, perhaps with some translation, if parking standards are construed differently.

Second, we need to know the current and planned fraction of parking demand due to residents, as opposed to visitors. Existing parking standards implicitly or explicitly make allowances for occasional visitors who may share non-dedicated parking spaces with residents. The greater the visitor fraction is, the greater the parking standard must be for a given vehicle availability. In this research, we neglect visitor parking because of a lack of data. Vehicle availability projections created here can be adjusted according to appropriate estimates of visitor parking demand as they become available.

Third, we need to know the current and planned fraction of parking demand that is or will be accommodated off-street. Drivers are prone to use on-street parking depending on its cost relative to off-street parking. This applies to visitors and to residents as well. Appendix B presents a preliminary analysis of how the availability (or unavailability) of off-street parking relates to household vehicle ownership. For the purposes of this analysis, we assume that residents of future developments will be presented with the same patterns of on- and off-street parking costs as currently exist. The results in Appendix B and further analyses could be employed to modify that assumption in the future, if need be.

Fourth, we must specify how existing patterns of parking supply should change. It may be a desirable planning goal, for example, to encourage transit use for a particular residential project or throughout a municipality or region. Reducing residential parking supply, and thereby increasing the time and/or monetary cost of vehicle ownership, may help advance that goal. For this research, we assume that the goal is to duplicate existing patterns of parking supply and vehicle ownership. As with the previous assumptions, a different situation could be modeled with straightforward adjustment of the vehicle availability projections developed here.

In summary, we link existing patterns of vehicle availability to future minimum residential parking supply by neglecting visitor parking needs; assuming that current patterns of on-street versus off-street parking supply will persist into the future; and assuming that the regulators' intent is to duplicate existing patterns of vehicle availability. The balance of this chapter is aimed to identify the key dimensions of these vehicle availability patterns. It identifies environmental and demographic characteristics that relate to vehicle availability, by reviewing the literature on forecasting and explaining household vehicle availability analysis. The chapter concludes by synthesizing the studies' findings into guidance for this dissertation research.

Two fields of transportation analysis

Forecasting travel behavior

The federal government catalyzed the first transportation analysis and forecasting in the U.S. Responding to concerns about the explosion of suburban housing after World War II, the Federal-aid Act of 1944 provided the first federal funding for urban highways, and also advocated transportation planning (Jones, 1998). The Federal-aid Act of 1954 made the first federal grants to metropolitan planning agencies to promote regional cooperation and planning; the Highway Act of 1962 made cooperative, continuous, and comprehensive transportation planning a prerequisite for urban areas with populations over 50,000 to receive federal highway funds (Solof, 1998).

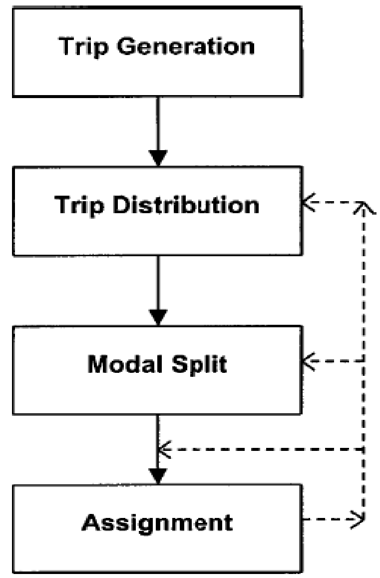

Figure 2.1. The four-step planning process (Boyce, 2002)

Consequently, the 1950s marked the first substantial travel demand forecasting in the US. The State of California's travel forecasting program began its work then (Jones, 1998). In 1959, the Chicago Area Transportation Study printed for perhaps the first time what would become the dominant paradigm in urban travel demand analysis and projection: the four-step approach (Boyce, 2002). The four-step approach is a sequential approach for estimating network loading: first, use household characteristics in a given location to estimate trip generation rates; second, distribute those trips to destinations; third, select a transportation mode for each trip; fourth, select a route in the multimodal network. Although methods for computing and connecting the models in each step have been thoroughly refined, the four-step approach remains the basis of travel forecasting practice today (Boyce, 2002).

Explaining travel behavior

Forecasting methods have little to say about why different geographies engender different travel behavior. Scholars from a range of fields—engineering, economics, psychology, and others—have tried to explain travel behavior, the argument being that understanding the fundamental decision processes allows for more robust projections. It is well beyond of the scope of this work to review the whole body of explanatory transportation analysis. (See Pas, 1996, and Waddell, 2001, for reviews of subfields.) The relatively recent literature on the relationship between land use and travel behavior, however, warrants discussion here.

The growing awareness of the costs of sprawl, starting in the 1990s, spawned a movement advocating "smart growth" and "new urbanism." Although the two terms are not identical, they overlap quite a bit, and entail reducing automobile travel and increasing the use of alternative modes. Researchers have completed scores of studies to evaluate the potential for land-use interventions to change travel behavior. (See Crane, 2000, and Ewing & Cervero, 2001, for reviews.) This body of work, outlined below, will inform the present research.

For the purposes of the present research, previous findings on household vehicle availability are of most interest. Here, the forecasting literature has an advantage. In the four-step model, household vehicle availability is an essential element of the sociodemographic inputs to the trip generation models. In the explanatory literature, by contrast, household vehicle availability is usually a by-product of analyses of more fundamental household characteristics (e.g. income, persons in household, age) and trip-taking behavior. Table 2.1 contrasts the two approaches.

Table 2.1. Contrasting two approaches to travel analysis

	Forecasting	***Explanatory***
Focus	Trip-based	Activity- and/or behavior-based
Goal	Improve methods for acceptable forecasts	Relate fundamental decision processes to manifest behavior
Model structure	Segmented	Integrative
Role of vehicle availability	Essential	Secondary

The present research creates and tests a vehicle availability forecasting method appropriate for the development of parking standards. Therefore, both the forecasting models and the explanatory analysis must guide this work. Insights from the explanatory modelers will lead to a method that attends to household travel investment decision processes, which is therefore most valid for extrapolation in time and space. The existing forecasting models point this work toward the most influential correlates with household vehicle availability, given a limited budget for data collection.

Forecasting models

The earliest forecasting models analyzed data at the zonal level to accomplish their task. Such "aggregate models" lack explanatory power because their foundational data do not allow the influences of separate variables to be distinguished from each other. Disaggregate models rely on microdata, measured at the household level, and allow for the study of interactions among variables. The disaggregated approach is currently the favorite, though aggregate models are still in use (Cambridge Systematics, 1997b).

Detroit's regional government uses an aggregate model to estimate vehicle availability. It cross-classifies survey data to estimate the fraction of households in a zone owning 0, 1, 2, or 3+ vehicles as a function of income, household size, and location (i.e., City of Detroit or not). This is combined with Census data to estimate number of households in each zone with each number of vehicles (Cambridge Systematics, 1997b). In 1995, the model was identified as a "best practice" approach (KJS Associates, 1995).

The Metro (Portland, Oregon) Auto Ownership Model, from 1989, is a disaggregate model using a multinomial logit structure. It includes the following predictors: number of persons in household, number of workers in household, income class of household, and number of employment opportunities within 30 minutes of transit time from the residence zone. The Metro model is heralded as "the state of the art of disaggregate models which include accessibility variables" (Cambridge Systematics, 1997b).

The Puget Sound Regional Council's model, developed in 1995, is an aggregate model that includes employment accessibility by mode (KJS Associates, 1995). In the first step, the distribution of households by income, persons in household, and workers in household, as measured at the Public Use Microdata Area (PUMA[7]), is computed and assumed to apply to all Traffic Analysis Zones (TAZs[8]) within the PUMA. This provides a preliminary estimate of the fraction of households in each TAZ that land in each vehicle availability class. The second step corrects those fractions with a logit-style factor derived from measures of the zonal average employment intensity and employment accessibility by mode.

In 1997, Cambridge Systematics developed a disaggregate vehicle availability model for the Delaware Valley Regional Planning Commission (DVRPC). They tested

[7] A PUMA is an area defined by the Census Bureau that must contain at least 100,000 people; to protect respondents' confidentiality, the PUMA is the smallest geographic unit linked with household-level responses. In New Jersey, PUMAs have an average population of 137,940, and an average land area of 121.6 square miles.

[8] TAZs, unless otherwise noted, are defined by the Census Bureau. They have roughly the same population as a Census tract, 4,000 people or so, but have boundaries defined by transportation related features in the landscape.

both multinomial logit and sequential logit models, where "sequential logit" refers to the estimation of a separate binary logit model for each increment in vehicle availability, representing the choice between 0 and 1+ vehicles, 1 and 2+ vehicles, and so on. The sequential logit model fit the data somewhat more closely (Cambridge Systematics, 1997a).

Table 2.2 summarizes the sequential logit model. "Jobs access ratio" is the ratio of the number of jobs within 80 minutes by transit divided by the number of jobs within 60 minutes by car. The table indicates that household income is the most statistically significant predictor for the two low-vehicle choices, while workers per household dominates the higher-vehicle choices.

Table 2.2. Sequential logit vehicle availability model: Coefficients and (z-statistics)

	0/1+	***1/2+***	***2/3+***	***3/4+***
Alternatives to automobile & relative costs				
Employment density	--	--	**-0.02** (9.5)	-0.04 (0.6)
Population density	**-0.03** (4.0)	**-0.03** (4.3)	--	--
Jobs access ratio	**-1.34** (2.0)	**-1.1** (2.7)	-0.71 (1.6)	--
Pedestrian environment factor	-0.44 (1.7)	-0.28 (1.8)	--	--
Activity demand				
Persons per household	0.10 (1.2)	**0.19** (3.2)	--	0.11(0.6)
Workers per household	0.12 (0.8)	**0.68** (7.1)	**1.03** (9.5)	**0.53** (2.9)
Income constraint				
Household income (natural logarithm)	**1.45** (10.0)	**1.38** (10.4)	**0.44** (2.5)	0.13 (0.3)
Persons less than lesser vehicles	--	**-2.7** (8.8)	**-0.88** (4.9)	-0.40 (0.8)
Constant	-0.28 (0.4)	**-4.2** (7.4)	**-4.2** (6.2)	**-3.6** (2.1)
N	1,993	1,837	1,162	308

Source: Cambridge Systematics, 1997b: Table 3.5. Items in bold are significant at the 5% level.

The New York Metropolitan Transportation Council (NYMTC) recently updated its disaggregate household vehicle availability model (Parsons Brinckerhoff Quade and

Douglas, 2005b). It is estimated as a multinomial logit model on data from household surveys conducted in 1997 and 1998—the Regional Travel-Household Interview Survey (RT-HIS). The most important predictors in the model are household income class, density (jobs and residents), access to jobs by car relative to other modes, and car sufficiency. The last item is a measure of the extent to which there is a household-level match between the number of automobiles and the need created by workers, nonworkers, and children. The model also includes residence area type-specific constants, where area types are defined by ranges of jobs and residents within 0.75 miles of the household.

The forecasting model reports are striking in their omission, for the most part, of discussions of model fit and the significance of various predictors used in the model. Such information is critical to informed decisions on predictor variables to use in any future model; any consensus on predictors could be born of expedience rather than explanatory power. We turn now to the academic, explanatory literature, which generally includes richer discussions of model parameters and offers more insight into causal relationships.

Explanatory models

To facilitate study-to-study comparisons, this review relies on insights from the broader travel behavior analysis literature. Crane (1996; 2000) suggests that the microeconomic theory of demand applies to trip-taking. This review applies the demand model to vehicle availability. The decision to keep a vehicle is assumed to be based on the costs of vehicle availability and its alternatives, the preferences of the decision-maker, and the income constraint.

Crane's (2000) review also suggests some of the key characteristics of urban form that likely influence vehicle availability decisions, thereby providing an organization scheme for the sections that follow. They consider studies that highlight the influences on vehicle availability of density, land use mix, and activity accessibility. The subsequent section addresses model estimation, another key issue in vehicle availability analysis. Finally, the growing literature on the relationship between residential location choice and vehicle availability is briefly reviewed.

Density

Schimek (1996) analyzes the impact of residential density on vehicle ownership, using linear regression on a nationwide sample taken from the 1990 National Personal Transportation Survey (NPTS). Table 2.3 summarizes the model. Population density is computed as the ratio of population in a zip code area to its total area, and is instrumented, to manage the assumed simultaneity of vehicle ownership and location decisions.

Schimek (1996) concludes that vehicle availability has a modest association with population density. See Table 2.3. His analysis shows that doubling a zip code area's density reduces household vehicle availability by 0.07 vehicles, all else being equal. As controls, he includes three common predictors from the forecasting models: workers and persons in households, and household income. He neglects measures of job accessibility and land-use mix. To the extent that these variables are correlated with density, their exclusion from the study should lead density's influence to be overestimated.

Table 2.3. Linear vehicle availability model, 1990 NPTS: N=15,916, r^2=0.38

	Coeff.	***t-stat.***
Alternatives to automobile & relative costs		
Transit within 3 blocks (I)	**-0.20**	-12.9
Population density (natural logarithm)	**-0.11**	-18.8
In a central city (I)	**-0.16**	-10.8
Activity demand		
Persons in household	**0.17**	32.1
Workers in household	**0.26**	27.7
Preferences		
Household head older than 64 (I)	-0.03	-1.6
Household head younger than 35 (I)	**-0.14**	-8.9
Income constraint		
Household income (natural logarithm)	**0.41**	43.7
Constant	**-2.21**	-22.8

Source: Schimek, 1996: Table 2. Items in bold are significant at the 5% confidence level. Binary indicator variables are marked with (I).

Use mix

Cervero (1996) examines the influence of mixed land uses on household vehicle availability using linear regression on 1985 American Housing Survey data for eleven metropolitan statistical areas. His model is summarized in Table 2.4. “Public services adequate” is defined according to the respondent’s opinion. “Distance from home to work” is endogenous to a two-stage system of simultaneous equations performed by instrumental regression.

Table 2.4. Linear vehicle availability model, 1985 AHS: N=9,804, r^2=0.21

	Coeff.	***t-stat.***
Alternatives to automobile & relative costs		
Public transit services adequate (I)	**-0.05**	3.3
Distance from home to work, one way in miles (I)	**0.01**	2.8
Residence in central city of MSA (I)	**-0.11**	7.6
Low-rise attached residential buildings within 300 ft of unit (I)	**-0.10**	5.2
Mid-rise multi-family buildings within 300 ft of unit (I)	**-0.27**	10.7
High-rise multi-family buildings within 300 ft of unit (I)	**-0.48**	6.9
Non-residential buildings with 300 ft of unit (I)	**-0.12**	2.7
Activity demand		
Persons in household	**0.11**	25.0
Income constraint		
Household income ($1000s)	**0.01**	41.3
Constant	**0.76**	177.0

Source: Cervero, 1996: Table 5. Items in bold are significant at the 5% confidence level. Binary indicator variables are marked with (I).

Cervero (1996) finds that having commercial uses nearby is associated with reduced vehicle availability, but more weakly than with high residential density or the demographic income and household size controls. However, the model is crude in some respects. Binary representations of land use may be inadequate. Also, the assumption that vehicle ownership is linearly related to household income is questionable.

Hess and Ong (2002) assess the extent to which the land use mix typified by traditional neighborhood development influences vehicle availability. They study the Portland, Oregon, area using an ordered logit model. Households are characterized by their income and size, and by the age (as a binary indicator), race (binary), and sex of householder. The household's choice of housing unit type is reflected by a variable distinguishing single-family units from units in multi-family buildings. Neighborhood variables include tract median income, tract household density, percentage white, land use mix (binary), transit accessibility (binary), proximity to a light rail corridor (binary), and a pedestrian environment factor. In the final model, which fit the data with a pseudo-r^2 of 0.39, only land use mix and household characteristics other than householder age are significant. Tract median income is marginally significant.

Accessibility

Kockelman (1997) develops two linear models of vehicle ownership to evaluate the importance of accessibility and other land use-related variables. She uses the 1990 San Francisco Bay Area Travel Surveys and land use data from hectare-level descriptions provided by the Association of Bay Area Governments to develop model parameters. Table 2.5 summarizes the models. Accessibility is computed with a gravity model formulation, where the friction factor is time-based with a form depending on the trip mode. The dissimilarity index is a hectare-level measure of use segregation. Land use balance is an entropy-style measure of the proportion of different land use types in a census tract.

Table 2.5. Linear vehicle availability model, 1990 SF BATS: N=8,050

	Excluding land use		***Full model***	
	Coeff.	***t-stat.***	***Coeff.***	***t-stat.***
Alternatives to automobile & relative costs				
Accessibility (all jobs)			**-9.1E-07**	-7.5
Land use dissimilarity			-0.11	-1.3
Land use balance			**-0.092**	-2.4
Population density			**-0.0026**	-14.0
Activity demand				
Persons in household	**-0.11**	-21.2	**-0.12**	-23.4
Income constraint				
Income per member ($1000s)	**0.0060**	19.1	**0.0055**	17.9
Constant	**1.02**	59.8	**1.27**	57.9
r^2	0.15		0.22	

Source: Kockelman, 1997: Table 2. Items in bold are significant at the 5% confidence level.

Kockelman (1997) concludes that land use variables exert a significant influence on household inclination toward vehicle availability. However, the model appears to lack important control variables such as number of workers or other household-level variables. Further, the fact that location and vehicle availability decisions are related is not accommodated.

Chu (2002) considers accessibility and land-use mix at the residence, along with environmental variables at the workplace, to estimate vehicle availability for New York City households. He develops an ordered probit model on data from the survey commissioned and used by NYMTC in its model development discussed above. See Table 2.6. Variables to characterize the built and travel environment are calculated at the TAZ level. The “automobile importance index” is a measure of relative accessibility to regional jobs. It is the ratio of the gravity model-based job accessibility by automobile to the sum of job accessibility over transit, walking, and automobile modes. The “mixed density index” is the product of residential density and employment density divided by their sum; it could be considered a density measure weighted by the degree of jobs/housing balance. Chu interprets “single-family house” as representing parking access.

Table 2.6. Ordered probit vehicle availability model, 1997/98 RT-HIS: N=3,397, r^2=0.33

	Coeff.	***z-stat.***	***Influence index***
Alternatives to automobile & relative costs			
Automobile importance index, for job access	**0.013**	7.0	<0.1
Mixed uses near residence: mixed density index	**-0.008**	-11.5	<0.1
Mixed uses near residence: entropy index	**-0.40**	-3.7	44
Single family house (I)	**0.38**	6.7	21
Reside in Brooklyn, Bronx, or Queens (I)	**0.17**	3.3	8
Reside on Staten Island (I)	**0.29**	5.2	17
Vehicle need at workplace (I)	**0.50**	8.6	29
Employment density at workplace	**-2e-4**	-3.1	<0.1
Work in Manhattan (I)	**-0.24**	-6.6	9
Activity demand			
Licensed drivers in household	**0.87**	30.5	25
Children in household	0.044	1.5	1
Preferences			
White-collar occupation (I)	**0.15**	2.8	8
Income constraint			
High income (I)	**1.04**	12.1	89
Middle income (I)	**0.65**	8.7	49
Constant	**-2.02**	11.4	
μ_1	**1.59**	39.6	
μ_2	**2.99**	56.3	

Source: Chu, 2002: Table 1. Items in bold are significant at the 5% confidence level.

Chu (2002) uses an influence index to illustrate the relative contributions of different variables to overall error reduction. The index in Table 2.6, proportional to Chu's version, is the absolute value of one thousand multiplied by the product of a predictor's standard deviation in the sample and its coefficient in the model. The most influential predictors are income, vehicle need at the workplace, number of licensed drivers, and housing unit type, followed by land use and other variables. The value of the influence measure is illustrated by the fact that whereas the mixed density index is the third most statistically significant predictor in the model, it is among the least influential.

Estimation method

Bhat and Pulugurta (1998) estimate vehicle availability using ordered logit and multinomial logit models. They use three US samples and one Dutch sample. They consider a range of predictor variables, and find only four that consistently influence vehicle availability: household income, number of workers, number of non-working adults, and neighborhood type.

More importantly, Bhat and Pulugurta (1998) systematically compare the performance of the two methods to the data. The models predict significantly different elasticities, indicating that they behave differently at the household level. Superior estimates of vehicle availability class and a better overall goodness-of-fit (controlling for the number of model parameters), for every data set, indicate that the multinomial logit approach is preferable to the ordinal logit approach over a range of household characteristics. The authors conclude that the behavioral assumption underlying multinomial logit, that choices are made among unordered alternatives, fits the household decision process better than the assumption underlying ordered logit, that vehicle availability is the manifest expression of a latent vehicle desirability function.

Location choice

Since the seminal work by McFadden (1978) decades ago, a great number of studies have investigated the household location decision. Guo (2004) reviews the literature, and identifies ten groups of commonly used predictors. All else being equal, she concludes that households generally prefer shorter commutes, affordable housing and lower crime rates. Households prefer space in terms of rooms, detached housing, and low residential density; larger households and those with children are especially desirous of space. Households tend to cluster in areas of their own race, socioeconomic status, and family structure. The effect of access to employment and services is ambiguous, as is the effect of school quality.

Waddell (2001) argues that for land use and transportation modeling to move forward, the two disciplines must explicitly confront the simultaneity of and interrelationships among residential location, job location, vehicle availability, and activity and travel choices. He provides an overview of work thus far to consider each element in the context of the others, offering 1,400 words on the subject. Vehicle availability earns 74 words, ending with these (p. 5):

> To date, little systematic effort has been made to treat vehicle ownership within a broader framework of household choice regarding housing location, workplace and daily travel patterns.

Unfortunately, Waddell and Nourzad's (2002) contribution does not directly confront the disconnect between vehicle availability and location choice. They specify a model of residential location, using data from the Salt Lake City area, that incorporates local (pedestrian) and regional accessibility measures, household composition, and vehicle availability, which is exogenous to the model. They find that households generally seek to reduce their housing cost burden, avoid densely packed housing, and have access to employment. Households that have many members, include children, own more cars, or have older household heads are especially averse to dense areas.

Sermons and Seredich (2001) estimate a joint multinomial logit model of vehicle availability and residential location using data from the San Francisco area. Distinct residential area types are identified via cluster analysis on TAZs. A single multinomial logit (MNL) model allocates households to a vehicle/location combination defined by crossing 0, 1, 2, and 3+ vehicles by four clusters. The model violates MNL's independent irrelevant alternatives assumption, but alternative model structures that were attempted, such as nested logit, did not reject the MNL specification. Household-level predictors are workers, non-working adults, teens, children, and household income by vehicle level. Residential cluster characteristics are persons per room, residential density by vehicle level, and the prediction of a utility submodel estimated with housing supply, housing price, accessibility, and race information. The model explains 30% of the variation in the data.

Cervero and Duncan (2002) use nested and multinomial logit models and a San Francisco Bay-area data set to study residential location, commute mode choice, and household vehicle availability. Data problems prevent them from including vehicle availability in the nested structure. Instead, they develop an independent MNL model of household vehicle availability. They characterize the household by its size, income, and race. They include the housing unit tenure (owned versus rented). For locational variables, they consider whether the house and/or job site are within one half mile of a rail station, the number of jobs within 30 minutes by car, and the number of jobs within 45 minutes by train. Only the job accessibility measures had no statistically significant relationship with vehicle availability. The model fits the source data with a pseudo-r^2 of 0.34.

Handy, Mokhtarian, and Buehler (2004) analyze the relationships among residential location, attitudes, and travel behavior using a variety of statistical methods applied to the survey respondents in eight Northern California neighborhoods. They estimate vehicle availability with an ordered probit model that includes demographic, land use, and attitudinal variables, all of which are exogenous to the model. The model fits the 1495 observations with a pseudo-r^2 of 0.21. No land use variables are significant when attitudinal variables are included. A preference for space is positively correlated with auto ownership.

Handy et al. (2004) also use ordinary least squares regression to estimate the change in vehicle availability by households that have recently moved. Demographic characteristics and changes therein dominate the model in terms of error reduction. In this model, land use effects survive the addition of attitude measurements: perceived changes in space and diversity of nearby use types are statistically significant, in the expected directions.

Gao, Mokhtarian and Johnston (2007) propose and test a system of simultaneous equations relating interdependent variables describing the built environment, demographics and automobile ownership. They develop a model using 2000 Census tract-level aggregate data for Sacramento county. They characterize the built environment by job accessibility, which is computed with a mode-independent gravity model. They find direct effects models of four endogenous variables as shown in Table 2.7.

Table 2.7. Standardized direct effects in the SEM

Predictors => Dependent variables	***Percentage of rental housing units***	***Median rent***	***Educational attainment***	***Household size***	***Job accessibility***	***Workers per capita***	***Income per capita***	***Autos per capita***
Job accessibility	0.64***	-0.21***					0.38***	
Workers per capita			0.29***		0.05*			0.56***
Income per capita			0.40***			0.76***		
Autos per capita				-0.60***	-0.80***	0.17***	0.37***	

Their work suffers from limitations that threatens its applicability to the present research. First, it draws on aggregate data rather than microdata, but implies conclusions about person-level behaviors. This is an example of the ecological fallacy, wherein zonal average characteristics and relationships are attributed to actors within the zone. Conducting analysis at the zonal level obscures the decision processes of the actors. The second issue is related: analysis is conducted on a per capita basis rather than a per household basis. The per capita basis is preferable to the extent that the individual actor is an independent decision-maker, rather than interdependent with other household members. Of course, household members generally share automobiles. The present research is aimed at projecting vehicle ownership at the household level.

Notwithstanding these concerns, Gao et al. (2007) draw conclusions that we should consider in developing this research. Table 2.7 shows that the number of automobiles per capita has no direct impact on job accessibility or income per capita, but directly positively influences workers per capita. The authors conclude that job accessibility affects autos per capita but not the other way around. This suggests that the household choice of residential location, at least relative to job centers, may be independent of the household choice of the number of vehicles to own. That is, it provides some evidence that household vehicle availability is exogenous to residential location. The results also suggest that vehicle availability may be endogenous to number of workers in a household.

Synthesis

The tables below summarize the studies and models reviewed above.

Table 2.8. Predictive vehicle availability models

Region	***Year***	***Level of analysis***	***Household variables***	***Environmental variables***	***Method***	***Comment***
Detroit	1984	Zone	Income (5) Persons	Location (2)	Cross-classification	"Best practice" but crude
Portland, OR	1989	Household	Income (4) Persons Workers	Jobs within 30 min.	MNL	
Seattle	1995	Zone	Income (4) Persons Workers	Jobs within 10 min. by foot Jobs within 30 min. by transit Jobs within 6 miles of urban centers	Cross-classification + logit-style correction	Recent aggregate model
Philadelphia	1997	Household	Income (log) Persons Workers	Job density Pop. density Transit vs. auto job access Pedestrian environment	MNL & sequential logit	Sequential logit slightly preferred
New York City	2005	Household	Income (3) Workers Non-working adults Children	Job + household density Area type: jobs and people nearby (11)	MNL	Includes area types defined to fit the data (likely not transferable to other samples)

Note: Numbers in parentheses indicate the number of levels in a predictor variable.

Table 2.9. Explanatory vehicle availability models: summary

Data source & scope	***Household variables***	***Environmental variables***	***Method***	***Data fit***
1990 NPTS – nationwide (Schimek, 1996)	**Income (log)** **Persons** **Workers** **Age of head(3)**	**Transit nearby (2)** **Pop. density (log)*** **Central city (2)**	Linear	0.38
1985 American Housing Survey – 11 MSAs (Cervero, 1996)	**Income** **Persons**	**Transit nearby (2)** **Commute distance*** **Central city (2)** **Low-rise res. nearby (2)** **Mid-rise res. nearby (2)** **High-rise res. nearby (2)** **Non-res. nearby (2)**	Linear	0.21
1994 Portland (OR) Household Activity Survey (Hess & Ong, 2002)	**Income** **Persons** **Single-family residence** **Race of head (2)** **Sex of head (2)** Age of head (2)	Median income Household density % White **Land use mix (2)** Pedestrian environment Transit nearby (2) Light rail corridor (2)	Ordered logit	0.39
1990 San Francisco Bay Area Travel Surveys (Kockelman, 1997)	**Income per person** **Persons**	**Job accessibility** Land use mix (hectare) **Land use mix (tract)** **Pop. density**	Linear	0.22
1997 RT-HIS – all NYC boroughs (Chu, 2002)	**Income (3)** **Licensed drivers** Children **White-collar occupation** **Single-family residence** **Need vehicle at workplace (2)**	**Job access by auto relative to other modes** **Land use mix at residence** **Borough of residence (3)** **Work in Manhattan (2)** **Job density at workplace**	Ordered probit	0.33
1990 MTC survey – San Francisco area (Sermons & Seredich, 2001)	**Workers** **Non-working adults** **Teens** **Children** **Persons per room**	**Pop. density**	MNL: vehicles & res. location type	0.30
2000 San Francisco Bay Area Travel Surveys (Cervero & Duncan, 2002)	**Income (3)** **Persons** **Race of head (2)** **Owned unit (2)**	**Transit near residence (2)** **Transit near work (2)** Jobs within 30 min. by auto Jobs within 45 min. by transit	MNL	0.34
2004 custom survey of eight Northern California neighborhoods (Handy et al., 2004)	**Income** **Persons** **Workers** **Persons of driving age** **Disability (4)** **Sex of head (2)** **Owned unit (2)** **Car dependent attitude** **Driving-safety attitude** **Accessibility preference** **Space preference**	Numerous measures of neighborhoods and perceptions thereof were tested and found insignificant	Ordered probit	0.21

Notes: Numbers in parentheses indicate the number of levels in a predictor variable. Items in bold are significant at the 5% level. Asterisks indicate instrumented variables.

This chapter's review considers vehicle availability research in terms of the influence of density, land use mix, job accessibility, and location choice. It presents a variety of estimation methods and specifications used in the transportation modeling literature. It suggests a few practical observations.

Practical modeling considerations

First, vehicle availability, as it relates to location in a built environment, has been the central focus of relatively little research. Instead, the great majority of research has aimed to estimate vehicle availability as a means to predict travel behavior; vehicle availability tends to be treated as a sidebar. Handy et al. (2004) assert that "[t]he connection between neighborhood design and auto ownership has not been extensively studied."[9]

Second, there is some confusion among vehicle availability modelers about what constitutes a noteworthy effect. Kockelman (1997) concludes that the impact of land use on vehicle availability is significant, owing to the statistical significance of residential density, land use balance, and job accessibility in her model. Handy et al. (2004) consider standardized coefficients to conclude that land use is much less influential than demographic variables. Chu (2002) develops an influence coefficient for his ordered probit model results, analogous to a standardized coefficient in linear models, and reaches the same conclusion.

[9] Interest in Location Efficient Mortgages (LEMs) has spurred some analysis focused on vehicle availability. The premise of LEMs is that households in locations near transit, jobs, and services can meet their travel needs with a lesser number of automobiles than is typical. The theory, then, is that households in these locations may own fewer cars, incur lower transportation expenses, and direct the savings toward increased mortgage payments. However, the most cited analysis supporting LEMs uses few predictors and uses a TAZ as its unit of analysis, which largely precludes analysis of household vehicle availability decisions (Holtzclaw, 1994; Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002).

Analysts using the language of "influence," considering standardized coefficients, are focusing on explaining variance. The standardized coefficient is the product of a predictor's model coefficient, its sample standard deviation, and the reciprocal of the dependent variable's standard deviation. For a linear model with one predictor, this equates to Pearson's r.

A statistically significant association between an independent and dependent variable in a regression model can lead to a small proportion of variance explained in two limiting cases. In the first, a small but consistent relationship exists between the variables, while there is substantial variation in the independent variable. For example, consider a model of housing unit price. It might be the case that the number of children in the household, which varies substantially among households, consistently but slightly increase willingness to pay for extra floor area in the housing unit. In the limiting second case, a rare variation in the independent variable is associated with a substantial variation in the dependent variable. For example, it might be that households near transit, given that the local density of retail services exceeds a certain threshold, and given that that transit accessibility to jobs exceeds another threshold, are willing to pay an extra 50% per unit of living area. A tiny fraction of the sample would be very susceptible to the interaction of retail density, transit job accessibility. The coefficient would be highly significant, but the proportion of variance explained would be negligible.

Location in a land use/transportation context may or may not be consistently "influential" on vehicle availability, depending on the sample. But there is ample evidence that it is "significant." Whether we consider density, use mix, accessibility to activities, or a combination of the three—the usual situation in practice—location consistently affects household vehicle availability.

Third, household choices about the type of housing unit seem to bear on vehicle availability. Studies reviewed here use a housing unit's detached status as a measure of parking supply, and find a significant association with vehicle availability (Chu, 2002; Soltani, 2005). Relatedly, Handy et al. (2004) find that a preference for space is associated with greater vehicle availability.

Fourth, the literature indicates some disagreement about the proper way to account for the feedback between the automobile ownership decision and the residential location decision. Schimek (1996) and Cervero (1996) use instruments in their regressions; they instrument different measures of residential location, however. Other efforts to estimate a vehicle availability model with residential location as endogenous, through nested logit and other approaches, have met little success[10]. The forecasting models and most land use/transportation researchers treat location as exogenous to the vehicle availability decision, and this is supported by some recent research (Gao et al., 2007).

Fifth and finally, no consensus has emerged on the most appropriate estimation technique for vehicle availability analysis. Explanatory modelers have increasingly used multinomial logit, and there is evidence to support that decision (Bhat & Pulugurta, 1998). Nonetheless, experienced analysts continue to use ordinal approaches as well (Handy et al., 2004). There is evidence from the forecasting modelers that a sequential logit approach bests MNL (Cambridge Systematics, 1997b), but sequential logit is not popular among explanatory modelers. Also, some explanatory modelers are returning to

[10]However, see Bhat and Guo (2005) for a mixed MNL/ordinal logit model.

linear approaches, to help them directly confront endogeneity using structural equation modeling (Cao, Mokhtarian, & Handy, 2007; Gao et al. 2007).

A working theory of vehicle availability

In addition to leading to the foregoing practical observations, this chapter offers the basis for a working theory of vehicle availability. Figure 2.2 illustrates the conceptual model employed in this research, which is described below.

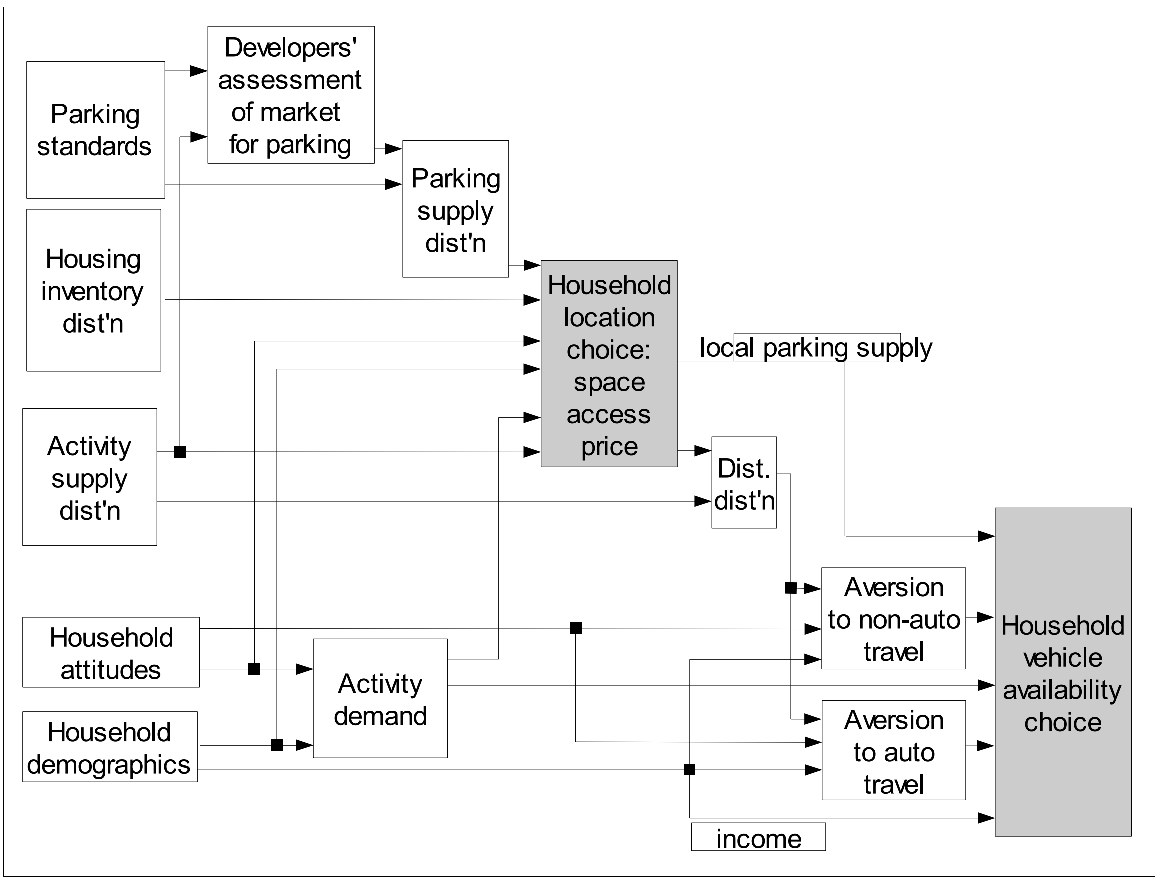

Figure 2.2. Conceptual model of households' decisions on vehicle availability

Chapter 1 generally discusses the relationship between residential parking standards and the amount of parking supplied. Here we clarify that discussion. Parking standards—specifying a minimum allowable number of parking spaces—are set according to regulators' best judgment. The developers' teams create their own assessments of the value of parking supplied in a residential project, influenced in their judgment by the regulators' standards and by local conditions. In some cases, banks require more than planning regulators. Also, developers may choose to provide additional parking beyond what is required or otherwise necessary, in the interest of accelerating approvals. The hope may often be that the layperson planning board would consider any additional parking, regardless of the standard, as a bonus. Rarely, developers present expert testimony to request a variance, the permission to provide less parking than the standards suggest. The result of this process is that parking minimum standards influence but do not strictly determine off-street parking supply at a residence. Other parking may also be available on-street or at nearby lots.

The housing location choice is considered a consumption decision, where the location represents a bundle of spaciousness and access to activities, following Cao et al. (2007). The choice is made from the set of available options, defined by the geographic distribution of housing stock, including its parking characteristics, and the related distribution of activity opportunities such as jobs and services. A household's desire for space is driven by attitudes and demographics such as household size and especially number of children. A household's desire for access to activities is called out in Figure 2.2 as the activity demand, which is driven by attitudes and demographics such as number of workers.

The household vehicle availability choice is a consumption decision aimed to meet the demand for activities, subject to the distribution of travel distances (or more generally, frictions) to those activities, with minimum cost. The degree of household demand for activities outside of the home drives vehicle need; however, its effect is moderated by a household's aversion to travel by mode. To the extent that household members are inclined and able to meet their demand for activities by non-automotive means, the relationship between activity demand and vehicle availability is weakened. For example, household vehicle availability should be less sensitive to the number of workers in a household well served by transit, or in an area with thoroughly mixed land uses, than in a remote household.

Household location also bears on the cost of accessing and using parking, in dollar and/or difficulty terms. Where ample off-street parking is supplied, parking is relatively cheap. Where access to parking is easy, as for single-family detached houses with driveways or attached garages, we can consider the cost of using parking to be zero. Where parking is shared, however, in on-street situations or where housing is served by residential parking lots, access to parked vehicles is more cumbersome.

The willingness to endure the monetary and nonmonetary costs of keeping and using an automobile is driven by household income. Generally, greater income should lead to an increased number of household vehicles. However, in urban situations this relationship may be weaker, as using an automobile becomes more burdensome in time terms while higher-income households may be more likely to hold professional jobs in urban cores served by transit.

Conclusions

The main goal of this research is to create a scientifically sound, practical method for forecasting household vehicle availability, for the purpose of land-use regulation. For maximum credibility, it should address all theoretically and empirically important predictors of vehicle availability. To be workable, it should sparingly define "theoretically and empirically important," bearing in mind the limited data available to regulators. It must attend to the competing virtues of expedience and comprehensiveness.

The next step in this research is to explore the relationships among household vehicle availability and the housing choices generally available to land-use regulators: location and housing unit type. The study is guided by the foregoing review as follows.

1. It must consider activity demand and other preferences, relative costs of alternatives to vehicle availability, and the income constraint.
2. It must reflect the finding that density, land-use mix, and employment accessibility have consistently significant associations with vehicle availability.
3. It must highlight the effects of urban environments. Residential parking requirements that neglect the influence of location—assuming complete or average auto dependence—are most problematic where alternatives to auto travel are readily available and/or auto ownership or use is burdensome. In a statewide or regional sample, these urban households will represent only a small fraction, and their choices will have a small impact on overall model error. Focusing on influence—reduction in overall model error—rather than statistical significance obscures location-related effects.

The next chapter follows these maxims as it considers household vehicle availability.

Chapter 3. Vehicle availability and practical housing unit descriptors

The express goal of this research is to develop a practical method for developing context-sensitive residential parking standards, which results in an improvement over current methods. The previous chapter outlined a comprehensive approach to estimating vehicle availability, moving us toward improvements through context-sensitivity: It identified significant predictors from among environmental, demographic, attitudinal, and residential choice variables from the literature. It also yielded a conceptual model of vehicle availability. Whereas the previous chapter centered on the prerequisites for a context-sensitive method of estimating parking demand, this chapter focuses on practicality.

This chapter presents analyses aimed to create a practical method. The first section presents a working definition of practicality. The second section reviews existing parking standards and argues that bedrooms, unit type and location are appropriate and sufficient for the method. The third section demonstrates that, in north and central New Jersey at least, all three variables–bedrooms, unit type and location–are necessary to capture substantial variation in household vehicle availability. The fourth section uses linear regression in an omitted variable bias framework to evaluate the direct and indirect relationships among our regulation-appropriate variables and household vehicle availability. The fifth and final section addresses the question of the geographic level at which household location must be defined. It suggests that the Census block group is the best choice of geographical unit. By virtue of the work presented in these five sections, we prepare to propose and evaluate a method for projecting household vehicle availability. That method and its validation are presented in Chapter 4.

On practicality

The context for implementing new parking standards is decidedly one where group decision-making dominates. Developers, along with their lawyers and engineers, present and defend their proposals for new housing projects to boards of laypeople—planning boards, zoning boards of appeal, town councils, and the like—who are in turn informed by their own experts. Roughly speaking, this is a situation that Andrews (2002) refers to as joint fact-finding: "the activities and perceptions of technically trained analysts working in a group decision support context." (p. xiv)

Andrews (2002) argues that the essential distinction between analysis in support of joint fact-finding and traditional technical analysis lies in the communicative context. Power trumps knowledge in group decision processes. To have an impact, therefore, the knowledge produced by analysts must be communicated in such a way that it can be adopted by powerful parties. The joint fact-finding cases that Andrews reviews involve analysts who interact to some degree with policy makers. In this case, however, there is essentially no interaction. Parking standards are published, and later used by municipal and consulting engineers who have no opportunity to interrogate or influence the analysts. This makes effective communication all the more important.

Andrews (2002) derives eight lessons for successful analysis to support joint fact-finding. The lessons center on communicating about the analysis to ensure maximum adoptability: the analysis must be readily understood, accepted, and implemented. See Table 3.1.

Table 3.1. Lessons for analysts supporting joint fact-finding

Goal	Lesson
Understanding	Rely on inductive reasoning in analysis
	Share information widely
	Persuasively translate analytical results
Accepting	Actively manage normative content in the analysis
	Broaden the analytical scope
	Perform cross-disciplinary reviews of results
Implementing	Marry analytical work to decision process
	Enjoy support of those in power

Source: Adapted from Andrews, 2002, p. 15.

The guidance summarized in Table 3.1 can be applied to the current research to varying degrees. Some lessons apply strictly to post-analysis communication, while others apply strictly to the analysis. For the sake of concision, I discuss here only those lessons that bear on the execution of this research[11].

Relying on inductive reasoning is important because different users of analysis results arrive at the group decision-making context with different theories. A purely theory-driven analysis can be limited, therefore, in its ability to forge common understanding. (On the other extreme, analysis that entirely excludes theory is also difficult to use because generalizing necessitates theory.)

Similarly, managing normative content of the analysis avoids conflicts in its interpretation: Normative content is based on value judgments that will not necessarily be shared by all parties to the decision. The concern about normative content applies much more to the design of an administrative process to use new parking standards than it does

[11]This discussion is drawn from Andrews (2002).

to the analytical process to create the standards. It is not a primary concern here, but important to bear in mind nonetheless.

Andrews calls on analysts to broaden their analytical scope, by which he means to avoid defining the problem so narrowly as to exclude some stakeholder interests. This guidance does not apply here, as the problem is defined a priori: create more accurate residential parking standards by incorporating context sensitivity. The new standards will have numerous implications, relevant to different stakeholders. Following Andrews's advice, the broad range of implications should be considered as the administrative process in which the new standards are embedded is designed. That is beyond the scope of this work.

Successful analysts in joint fact-finding also perform cross-disciplinary reviews of results. These reviews are not part of the present research, but to be useful, this research must stand up to subsequent reviews. This in turn depends on what Andrews calls the adequacy of the analysis—effectively its scientific soundness. A scientifically sound method should entail a transparent process to process data of known quality to produce estimates along with the uncertainty in those estimates. In addition, Andrews's criterion of “value” applies here: in this case, a valuable analysis produces accurate estimates with low uncertainty.

Finally, successful analysts in joint fact-finding situations marry their analytical process to the decision process. To have an impact, the analytical results must be inserted into the decision process. This happens through a process of communication that is facilitated when the analytical process was developed with the institutional context in mind. When the analyst does his or her work while considering which parties, with what set of interests and influence, will be interacting, along with the rules and norms that guide those interactions, he or she can work to ensure that the results can be easily introduced into the group decision-making context. This simplifies the purely communicative task that follows the technical analysis.

In summary, Andrews's (2002) guidance demands that this method exhibit the following qualities.

1. Inductive: The method should be guided by theory but rely heavily on observation.
2. Adequate & valuable: The method should process data in a scientifically sound way to create accurate estimates with low uncertainties.
3. Married to decision process: The method should reflect the group decision-making context in which the resulting new standards will be used.

The balance of this chapter presents preliminary analyses aimed to ensure that the method is scientifically sound. The first and third criteria above are considered in Chapter 4, where the method is presented.

Review of existing residential parking standards

Many of the studies reviewed in Chapter 2 include demographic predictors that are likely to change whenever a residence changes hands, such as householder race and income. Land use regulations, on the other hand, must respond only to fixed attributes of development. Given that the task at hand is to create an improved method for developing residential parking standards, the disconnect between research and regulation variables raises the question of what residential development characteristics to use in our method. Residential characteristics with a strong relationship to household vehicle availability, while being unchanging and readily measurable, should be the best candidates. This section draws on a review of existing parking standards, along with insights from Chapter 2, to propose the residential development characteristics around which we will build a method for developing parking standards.

Seattle

The City of Seattle considers a number of factors in setting minimum parking requirements for residential development (City of Seattle, 2006). Single-family units, regardless of location and occupants, must have a minimum of 1 parking space provided. The default requirement for multifamily units is an increasing function of number of units on the parcel: 1.1 spaces per unit for 2 to 10 units, up to 1.25 spaces per unit for more than 60 units on the parcel. Additionally, the parking requirement is adjusted by an linear increment for floor area per unit: at 500 square feet, there is no increment, and at 1250 square feet and above, the increment is 0.15 spaces per unit. Where half or more of all units have 3 bedrooms, an additional 0.75 spaces per 3-bedroom unit is required. Any 4-bedroom unit requires an additional space, in addition to the unit number- and floor area-based calculations above. Even without considering exceptions, Seattle's code is quite sophisticated.

Location is a key determinant of Seattle's parking standard exceptions. For example, there is no minimum parking supply requirement for housing of any sort in downtown zones. Also, seven neighborhoods or "urban villages" in the "Center City" have reduced standards for multifamily housing. Conversely, units in the University District have higher, bedroom-sensitive requirements than the default. This reflects the likely make-up of those units—unrelated students whose number depends strongly on bedrooms, and whose inclination to own vehicles is relatively independent of roommates' vehicle ownership. The effects of other household characteristics on parking standards generally depend on neighborhood location.

Income is also important in Seattle's code. Multifamily units rented to tenants with less than 30 percent or 50 percent of the area median income qualify for reduced parking standards. The amount of the reduction depends on the location of the unit, whether the tenant is elderly and/or disabled, and the number of bedrooms in the unit.

Portland, Oregon

The City of Portland has a less sophisticated but perhaps more aggressive set of parking standards than does Seattle (City of Portland, 2005). Its default minimum requirement for multifamily units is 1 space per unit, less than Seattle's lowest, and Portland does not increase the requirement for larger floor area or greater numbers of bedrooms. Similarly, although Portland does not allow location-specific reductions for income, single-room occupancy (SRO) hotels have zero minimum parking requirements throughout the city.

Location does factor into Portland's standards, however. Portland divides the city into 17 zones. For residences in six of those zones, there is no minimum parking requirement. Two additional zones have reduced requirements: zero spaces per unit for parcels with 3 or fewer units and 0.5 spaces per unit otherwise. Further, one zone has a parking supply *maximum* of 1 space per unit. Also, for any residential development in the city that is within 500 feet of a transit street with service intervals no more than every 20 minutes in peak hours, the minimum parking requirement is zero.

Greater Portland

Oregon's Transportation Planning Rule directs local governments to reduce automobile travel and limit the construction of parking spaces in their management of new development (Metro, 2004). To that end, the regional government that manages planning regulations in the greater Portland area, Metro, has established residential parking standards for cities and counties in its jurisdiction. The affected governments are not allowed to require more than the given number of spaces per residential unit constructed. Metro's standards are as follows: 1 space per unit for hotel/motels, single-family detached units and 1-bedroom units encompassing less than 500 square feet. For multifamily and townhouse developments, the standards depend on bedrooms: 1.25 spaces per unit for 1 bedroom, 1.5 spaces for 2 bedrooms and 1.75 for three bedrooms. Metro does not require constituent governments to reduce standards in particular locations according to transit access or other factors, but it does not prohibit them from doing so, either.

Montgomery County, Maryland

Montgomery County, Maryland, offers an example of a county-wide residential parking standard (County of Montgomery, 2005). For units in an apartment hotel, the parking requirements range from one space per unit for zero-bedroom units up to two spaces for units with three or more bedrooms. Multifamily units are also required to provide between one space per unit, for zero-bedroom units, to two spaces for three or more bedrooms. Single-family units, including townhouses, must provide two spaces. The standards are significantly reduced, and still bedroom-dependent, for housing for elderly or disabled people.

Montgomery County's base standards can be reduced depending on the unit's location. Senior and/or disabled housing parking requirements are reduced sequentially: by 5% if units are within 1,000 feet of a Metrorail station entrance; by another 10% if an adequate private shuttle service is provided; by up to another 20% if units meet the legal definition of “moderately priced”; and by 20% for assisted living. Other residences can earn parking requirement reductions sequentially as well: by 10% if units are in a central business district or a “transit station development area”; and by another 5% if units are within 1,600 feet of a Metrorail station entrance.

New Jersey

The State of New Jersey offers an example of a statewide parking standard (State of New Jersey, 1997). The parking requirements include no explicit reference to location; however, the differentiation in unit types does imply differences in the local environment. For example, garden apartments and high-rise apartments are treated separately, and have standards for one-, two-, and three-bedroom units, where the high-rise requirements are lower than the garden apartment requirements. (See Table 3.2 for details.) Also, municipalities are welcome to create their own special area standards. The City of Hoboken is among those that has done so–its standards include prohibitions on off-street parking in some parts of the city. Finally, these standards do not apply where residential and nonresidential uses share parking facilities (Goldsmith, 2007).

Table 3.2. New Jersey's Residential Parking Standards

Housing unit type	***1 BR***	***2 BR***	***3 BR***	***4 BR***	***5 BR***
Single-family detached or two-family		1.5	2.0	2.5	3.0
Townhouse	1.8	2.3	2.4		
Garden or mid-rise apartment	1.8	2.0	2.1		
High-rise apartment	0.8	1.3	1.9		
Assisted living	0.5				

Source: State of New Jersey, 1997: Table 4.4
Notes: Multifamily standards include 0.5 spaces per unit for visitor parking, which may be accommodated on- or off-street.

Table 3.3 summarizes the residential parking standards reviewed above. The most common indicators in Table 3.3 and elsewhere (Davidson & Dolnick, 2002) are unit type[12], bedrooms and location. These are essentially fixed properties of a housing unit. Although single-family detached dwelling units can add a bedroom with relative ease, it is all but impossible for attached housing units to do so.

Table 3.3. Summary: variables used in selected parking standards

Jurisdiction	***Parameters***	***Jurisdiction***	***Parameters***
Seattle, Washington	Unit type Floor area per unit Bedrooms Income Age Location	Metro: Area around Portland, Oregon	Unit type Bedrooms Floor area per unit
City of Portland, Oregon	Unit type Location	Montgomery County, Maryland	Unit type Bedrooms Age Disability Location
		New Jersey	Unit type Bedrooms

[12]The term "unit type" as used here refers to the number of units in a structure and/or descriptions such as "high-rise apartment" and "garden apartment."

Household income and householder age are less common in standards, but special standards for age-restricted housing and low- to moderate-income housing are not unusual, according to the discussion above and parking references with nationwide scope (Davidson & Dolnick, 2002). Income and age depend on the occupants of the unit, of course, and could change frequently. To allow age and income to be considered in setting parking standards, laws and contracts fix them to the housing unit, effectively making them characteristics of the unit.

Floor area may also be useful. Metro (governing metropolitan Portland, Oregon) and Seattle consider the floor area of multifamily units, which is as fixed as is the number of bedrooms. Researchers in Ontario found that total floor area was the best predictor of the total parking demand exhibited in a multifamily complex, followed by number of bedrooms and then number of units (T. P. Smith, 1983). The apparent rarity of unit floor area among parking standard regimes may well relate to the cost of collecting reliable data. As most geographically broad data sets are based on take-home surveys, measurements of unit size in those data sets are only as precise as volunteer respondents are willing to make them. It seems likely that many residents are unsure of their total living area. Given that floor area is a measure of unit size, as is number of bedrooms, and the latter is likely measured more reliably, we consider bedrooms preferable to floor area.

The household characteristics used in the regulations cited above share two essential traits: they relate to drivers of household vehicle availability prima facie, and they are physically or otherwise affixed to the unit. These two conditions are essential for effective vehicle availability estimates. Further, the most widely used household characteristics—unit type, number of bedrooms and location—are also easy to ascertain.

They can be measured reliably, allowing the regulation to be administered consistently. Any additional household characteristic to be used in setting parking standards must be justified in terms of the accuracy improvement it offers and the consistency of its influence.

The vehicle availability studies cited in Chapter 2 offer no clearly worthwhile additions to the set of household characteristics in Table 3.3. The studies include various environmental characteristics such as access to jobs and proximity to transit, all of which are bound to location. They also make use of a number of household-specific variables: household income, ownership status and number of persons of various sorts (workers, children, licensed drivers), and householder age, sex, race, and occupation. None of this personal data can be fixed to a household with three exceptions. Income and age have been included in parking standards above in a limited way, and could be here as well. Ownership status—rented versus owned—could be fixed by regulation in the same way.

This research is aimed to determine how location interacts with household variables to influence residential parking demand, with the ultimate goal of developing a *broadly* applicable method for setting residential parking standards. The foregoing review suggests that, to meet this goal, the method should rely on bedrooms, unit type and location. It does not specifically address the special cases of deed-restricted affordable or elderly housing, although the methods here could be modified to do so. Rental housing can be easily converted to owned housing—possibly changing the parking demand without official oversight. Taking a cue from the standards reviewed above, ownership status will also be neglected in this research. Based on the foregoing review, we contend that bedrooms, unit type, and location are appropriate and sufficient for the method under development here.

Impacts of regulation-appropriate variables on household vehicle availability

That leaves open the question of whether all three variables are necessary in our method. This study has already presented evidence that unit type, bedrooms and location influence vehicle availability. The parking standards reviewed above indicate a general acceptance among practitioners that the three variables bear on vehicle availability. Also, the studies cited in Chapter 2 explicitly test and find relationships between vehicle availability and various aspects of housing location and, in some cases, unit type. The relationship between bedrooms and vehicle availability is untested, but common experience with the housing market suggests that number of bedrooms is positively correlated with housing price and, therefore, income. Combine that with the link between income and vehicle availability demonstrated in Chapter 2, and we have an indirect link between bedrooms and vehicles. Notwithstanding this evidence, the question remains of *how much* unit type, bedrooms and location influence vehicle availability.

This is an essential question in preparing a new method for calculating parking standards. The development and implementation of a new regulation is expensive. Like many other investment decisions, it must be justified with a cost-benefit analysis. Does the benefit of capturing whatever interhousehold vehicle availability variation we can represent with the regulation-appropriate variables outweigh the cost of implementation?

This section demonstrates the extent of the association between household vehicles and our regulation-appropriate variables: location, unit type and bedrooms. The studies cited in Chapter 2 speak to the statistical significance of some of these relationships, while controlling for selected covariates. By contrast, this section assesses how much variation in average household vehicle availability is associated with variation in our chosen regulation-appropriate variables, ignoring all other factors.

At the PUMA: Location, unit type and bedrooms

Here we consider the associations between vehicle availability and unit type, bedrooms and location in the State of New Jersey. New Jersey is the most densely populated state in the country, and exhibits a wide range of built environments. It is bounded by two major employment centers—New York City and Philadelphia—and also hosts significant job concentrations within its borders, in cities such as Jersey City and in sprawling pharmaceutical campuses in central New Jersey. It is served by an extensive public transit system including trains and buses, as well as a massive road network. New Jersey makes an interesting case because of its activity intensity and land-use diversity.

This analysis is conducted using data from the Census Bureau, reported at the Public Use Microdata Area (PUMA) level. A PUMA is defined by the Census Bureau to contain no fewer than 100,000 residents. This level is set to ensure household confidentiality, as individual household responses to the long-form survey used in the Decennial Census are linked to the households' home PUMA before being released to the public. The PUMA is the smallest geographic unit at which publicly available household data on unit type, bedrooms and vehicles available are or can be tabulated[13]. Using data at the PUMA level offers the strength of comprehensive data on household composition and housing unit, but allows the responding household to be located within a

[13]The State Data Centers created by the U.S. Census Bureau can actually tabulate households in vehicles available x unit type x bedrooms x location for areal units as small as block groups. However, confidentiality concerns lead the Census Bureau to set the minimum cell size relatively high and the number of levels in each variable to a low value. As a result, special tabulations available from State Data Centers are not adequate for the purposes of this research.

transportation and land-use context in only a gross way. Table 3.4 summarizes the PUMAs in New Jersey.

Table 3.4. New Jersey's 61 Public Use Microdata Areas

		Area (mi^2)	***Population density (persons/ mi^2)***	***Average vehicles per household[1]***
Minimum		3.4	254	0.78
Percentiles	25	24.3	983	1.47
	50	60.3	2250	1.71
	75	138.3	5686	1.83
Maximum		633.8	35135	2.02

[1]Mobile homes, boats, RVs, tents and other non-structure residences are excluded.

Table 3.4 introduces a method of presenting distributions that we return to a number of times in this chapter. The practice of presenting quartiles rather than means and standard deviations is intended to illustrate as intuitively and compactly as possible the actual distribution of geographic entities' characteristics. In particular, in subsequent discussions we use the difference between 25th and 75th percentile values as a measure of dispersion, rather than the standard deviation. The percentile-difference is explicit about what fraction of the sample falls in the tails, whereas to infer the same information from the standard deviation would require knowledge of skew and kurtosis along with some calculations. So here we choose to trade a small loss of compactness for ease of interpretation.

Table 3.5 was created by computing average household vehicle availability by PUMA for the four unit type/bedroom combinations shown, after ensuring an adequate number of responses in the class. PUMAs containing fewer than 30 survey responses in the given unit type/bedroom combination were excluded on a case-wise basis; because the Census Bureau provides a 5% sample of the 1 in 6 households that completed the long form, some PUMAs did not meet the 30-response criterion despite their 100,000-person size. The lower bound on sample size was enforced to help ensure a reliable estimate of the mean.

Table 3.5 proxies location in a land-use and transportation context in terms of the residential density of the PUMA: the percentile score for each PUMA is computed according to its relative residential density. Chapter 2 reviews numerous studies that identify characteristics of the physical environment other than density, such as employment accessibility and land use mix, that have independent influence on vehicle availability. We limit the discussion of location here and later in the chapter to residential density for clarity of presentation.

Table 3.5. PUMA-average household vehicle availability by unit type and bedrooms

Percentile	***Single-family detached***		***10-19 units in structure***	
	3-bedroom	***4-bedroom***	***1-bedroom***	***2-bedroom***
25th	1.80	1.93	0.83	0.99
50th (median)	1.91	2.11	1.04	1.30
75th	1.95	2.19	1.16	1.42
Difference between 25th and 75th percentiles	0.15	0.26	0.33	0.43
N	60	61	51	45

Table 3.5 indicates substantial variation in household vehicle availability along all three dimensions. In each column, the differences among the rows shows the location-related variation in vehicle availability for a given unit type/bedroom combination. For example, the second column shows that the PUMA with the 25th percentile PUMA-wide average vehicle availability for 4-bedroom single-family detached units is 1.93, whereas in the 75th percentile PUMA, the average is 2.19 vehicles per household. In all but the 3-bedroom single-family case, the 75-25 percentile difference exceeds 10% of the median value. Also, the table shows greater inter-PUMA differences for units with more bedrooms, and for the attached units rather than the single-family detached residences.

The table indicates substantial vehicle availability variation according to number of bedrooms as well. For both unit types, the difference between the median vehicle availability for the greater number of bedrooms is more than 10% greater than the value for the case with fewer bedrooms. Also, at every PUMA percentile, the multifamily unit gains more vehicles from adding a bedroom than does the detached unit.

The table also shows that different unit types tend to have greatly different average vehicle availabilities. The 1-bedroom multifamily unit averages about half as many vehicles as the 3-bedroom detached unit, at every percentile level. Granted, this conflates the influence of bedrooms and unit type. For clarity, a comparison of two unit types with the same bedroom levels would have been preferable. However, that was not possible given the need for 30 respondents in each PUMA x unit type x bedrooms cell: 4-bedroom multifamily units and 1-bedroom detached units are quite rare in New Jersey.

This review of PUMA-level data suggests that location, unit type and bedrooms are independently useful for predicting household vehicle availability. However, this analysis is limited by the large size of PUMAs. Because they are much larger than the distance scale of changes in household vehicle availability, potentially significant locational effects are averaged away. It may be that this PUMA-level analysis underestimates the importance of location.

At the Census tract: Closer look at location, ignoring bedrooms

To get a better estimate of the importance of location, data from the 2000 Census Transportation Planning Package (CTPP) are analyzed here. The CTPP is a special data product based on the long-form responses collected from 1 in 6 households during the Decennial Census. Unlike the PUMS, the CTPP reports all long-form responses and it does not report disaggregated household-level data. It does include a number of cross-tabulations that address aspects of transportation-related behavior, however. Included among those cross-tabulations is one that indicates the number of households within a tract—a Census Bureau-defined area designed to hold a population of 4,000—that land in various levels of household vehicle availability and unit type. The analysis here uses data from that cross-tabulation for all 1,950 tracts in New Jersey.

Before data from the CTPP are used to calculate tract-average vehicle availability broken down by unit type, tracts with too few respondents in a unit-type level are excluded from analyses on a case-wise basis. Here the threshold minimum is 180 "equivalent" households. The CTPP reports estimates of actual numbers of households in each level in each tract. Given the 1 in 6 sampling strategy, 180 households in the CTPP is equivalent to roughly 30 survey respondents[14].

[14]The weighting factor is approximately 6 because of Census Bureau efforts to account for sampling irregularities such as nonresponse.

Table 3.6. Tract-average household vehicle availability by unit type

Percentile	***Single-family detached***	***2-4 units in structure***	***5+ units in structure***
25^{th}	1.78	1.00	0.54
50^{th}	1.94	1.25	0.95
75^{th}	2.09	1.49	1.21
Difference between 25^{th} and 75^{th} percentiles	0.31	0.49	0.67
N	1600	1818	1814

Table 3.6 shows the distribution of tract-average vehicle availability in New Jersey, broken down by unit type. Each column taken by itself indicates that for every unit type, household vehicle availability differs substantially from tract to tract. The 75^{th}-to-25^{th} percentile difference approximates the extent of the intertract difference. This difference increases as the number of attached units increases. That is, average household vehicle availability for units in larger buildings is more sensitive to location than it is for smaller and detached buildings.

The rows show that vehicle availability tends to decrease as the number of units attached to each other increases. At every percentile, units in larger in buildings have fewer vehicles available to them. As with the PUMA-level analysis, this table conflates unit type and bedrooms. Nonetheless, the vehicle availability differences are stark. Across almost all percentile/unit combinations, a one-level increase in building size is associated with a reduction in household vehicle availability of 0.3 or more.

To sum up this section, the analyses at the PUMA and the tract level show that each of our regulation appropriate variables contributes to household vehicle availability. Moreover, the vehicle availability differences are substantial. Consider the case of a 10-

unit structure composed entirely of 2-bedroom units. If that structure is located in the 75th percentile PUMA, its expected structure-wide vehicle availability would be (10 * 14.2 =) 14.2. Put the same structure in the 25th percentile PUMA, and we would expect it to have (10 * 0.99=) 9.9 vehicles on site. Regulate the 25th percentile-PUMA structure as if it were in the 75th percentile PUMA, and we require it to have (14.2 – 9.9 ~) 4 spaces more than necessary. Assuming those spaces are supplied in a surface lot, that amounts to about $80,000 in added initial cost[15], or $8,000 per unit, and this translates to a greater increment in unit price. Four surface parking spaces also consume about 1700 square feet, more than enough for another residential unit per floor of the structure. The potential revenue loss for the developer or added expense for the home buyer is substantial. In sum, the impacts of bedrooms, unit type and location are substantial: Each variable is necessary to the method under development here.

Relating regulation-appropriate variables to vehicle availability

We have concluded that unit type, bedrooms and location are the housing characteristics necessary and sufficient–in the sense that no additional, influential variable is appropriate to include–for the method under development here. However, the review in Chapter 2 illustrates clearly that household demographics influence vehicle availability decisions more than location within a particular land use and transportation context does. The residential unit choice variables of unit type and number of bedrooms are included in the studies cited in Chapter 2 only in the difference between detached and attached housing. Again, the impact of that difference is small compared to demographics. The dominance of demographics in the vehicle availability decision,

[15]This figure comes from slightly inflating the data in Table 1.1, which presents an estimated initial present value of the 24-year costs of surface lots at $19,700 per space, in 1997 dollars.

coupled with our inability to include demographics in a residential parking standard, puts us in a quandary. How much can we say about household vehicle availability if we know only a household's location and the unit type and number of bedrooms it chooses?

Data

To answer that question we must study how much we miss by leaving out the most influential demographic predictors. Therefore, we must draw on a data set that includes household demographics, location, unit type, number of bedrooms, and vehicles available. The Census Public Use Microdata Sample (PUMS) offers that data. The PUMS includes a broad range of household and person-level data, including vehicles available, unit type and number of bedrooms. Unfortunately, it locates respondents only to their Public Use Microdata Area (PUMA), which by design holds at least 100,000 people. As a result, household location information will be biased toward a regional mean.

We focus on New Jersey because it is the most densely populated state in the union, which fits our focus on urbanized areas where alternatives to automobile travel tend to be more widely available. To further support our interest in urbanized areas, we consider only the northern and central counties, which lie within the New York City metropolitan commuter shed. The sample is described in Appendix C.

In performing this study we follow the lessons from Chapter 2, to the extent the data allow. We include drivers of activity demand, preferences, the costs of vehicle availability and its alternatives, and the income constraint. We account for the effects of density, land-use mix, and employment accessibility. The following paragraphs outline the relationship of the variables used in this section's analysis to Chapter 2's lessons.

Working adults. The number of working adults is associated primarily with the demand for activity outside the home. Workers must travel to work, generally. Also, they tend to need services to maintain their employability, such as haircuts, dry-cleaning, etc.

We expect the number of workers to be positively associated with household vehicle availability. Studies reviewed in Chapter 2 find this to be true, controlling for other household characteristics such as income (Handy et al., 2004; Schimek, 1996; Sermons & Seredich, 2001).

Working adults are defined in the PUMS as people aged 18 or older who worked in the week preceding the Census or who looked for work in that time.

Nonworking adults. The number of nonworking adults is likewise related to the household's demand for activities outside the home. As such, we expect it to be positively associated with vehicle availability, all else being equal. Studies reviewed in Chapter 2 confirm this expectation (Handy et al., 2004; Schimek, 1996; Sermons & Seredich, 2001).

Nonworking adults are defined here as people aged 18 or older who did not work or look for work in the week preceding the Census.

Children. The number of children in the household is linked to demand for activity outside the household. However, the direction of causality is ambiguous. On one hand, greater numbers of children may lead to greater need for shopping of various sorts, participation in extracurricular sports, doctor's visits, etc. On the other hand, having children in the home may consume a nonworking adult's time and energy, and decrease his or her ability and inclination to participate in activities outside the home.

The ambiguous and complex relationship between children and activity demand is reflected by the way the New York Metropolitan Transportation Commission (NYMTC) Best Practices Model accounts for children in estimating household vehicle availability. The model responds only to the presence of children, not to the number of children. Further, the need for automobiles of nonworking adults in households with children is assumed to be less than in households without children, because the children are presumed to require care by nonworking adults (Parsons Brinckerhoff Quade and Douglas, 2005b).

In addition to its relationship with activity demand, household children are also associated with household preferences. There is evidence, for example, that households with children present are especially averse to crowded conditions (Guo, 2004; Waddell & Nourzad, 2002). In other, attitude-focused research, the preference for space is found to be positively associated with vehicle availability (Handy et al., 2004). From this line of reasoning, we might expect the number of household children to be positively associated with household vehicle availability.

We expect number of children to be weakly associated with vehicle availability. Studies reviewed in Chapter 2 bear this out. Chu (2002) finds only a marginally significant association between children and vehicle availability. Sermons and Seredich (2001) develop a 17-variable joint model of vehicle availability and residential location in which the number of children is the 15th most significant predictor.

Children are defined here as household members aged 17 or fewer years.

Household income. Household income relates to the income constraint on expenditures, according to the microeconomic model of household consumption choice.

We expect that greater household income is associated with greater household vehicle availability. Numerous studies confirm this expectation (e.g., Cervero, 1996; Cervero & Duncan, 2002; Chu, 2002; Handy et al., 2004; Hess & Ong, 2002; Kockelman, 1997).

Household income is operationalized here as the natural logarithm of annual income in 1999. Using the logarithm of income leads income to have a diminishing impact on vehicle availability as income increases.

Density. Density, land-use mix and accessibility all bear on the relative cost of alternatives to vehicle availability. Density of residences, employment or development is important in that it is associated with making automobile use more difficult by clogging road networks (Chatman, 2005). Local, pedestrian-scale accessibility speaks to the ability to get to jobs or services by walking. Regional job accessibility, on the other hand, indicates the relative importance of having a vehicle available to reach employment opportunities.

Land-use mix near the residence is closely related to job and service accessibility, the difference between mix and accessibility being largely in the nature of accessible activities. A single house or housing complex surrounded by services is likely to have those services be regional-scale specialized services, as most shoppers must reach the establishments by car. In places where there is sufficient residential density to support the nearby services, those services are more likely to be oriented toward a pedestrian market. For example, a downtown surrounded by housing is likely to host stores that meet basic needs such as a convenience store or pharmacy. By contrast, having an apartment complex situated next to a regional mall is unlikely to foster walking rather than driving. Some researchers capture the difference between these two cases by using land-use mix measures at different spatial scales (Kockelman, 1997).

As density, land-use mix, and local accessibility increase, the relative cost of driving rather than traveling via other modes increases. As a result, the relative benefit of vehicle availability falls, and we should expect that vehicle availability itself falls as well. Studies cited in Chapter 2 confirm this expectation (Chu, 2002; Kockelman, 1997; Schimek, 1996).

In this section, we use PUMA density as a proxy for land use mix and local accessibility. On average, high density PUMAs should have greater land use mix and higher average local job accessibility than lower density PUMAs. Drawing on Chatman's (2005) conclusion that density impacts travel behavior by making automobile travel more difficult, we use here an activity density that combines worker and residential populations and their impacts on the road network loading. Further, we take the natural log of this activity density before employing it in the model; each doubling of density leads to a scale-independent increment in expected vehicle availability. Finally, we create a z-score from the logarithm of the activity density. The computation of the density measure is summarized below.

$$LD = \ln\left(\frac{(number\ of\ PUMA\ residents + number\ of\ PUMA\ employees)}{(PUMA\ square\ miles\ of\ land)}\right) \tag{3.1}$$

$$density = \frac{(LD - mean(LD))}{(s_{LD})} \tag{3.2}$$

Unit type Unit type–single-family detached, single-family attached/townhouse, multifamily, etc.–relates to two of the fundamental drivers of household vehicle availability decisions. First, it relates to preferences, in particular, a preference for space and/or privacy. Generally, a greater number of attached units indicates a greater number of households sharing common areas such as parking lots and grassy areas. Households that put a higher priority on space should be more likely to choose unit types that offer more privacy from neighbors. Combine this with the observation that households that prefer space tend to have higher vehicle availability (Handy et al., 2004), and we are led to expect that unit types that offer more privacy should have higher average vehicle availability, all else being equal.

Second, unit type relates to the relative benefit of vehicle availability and use. We would expect single-family detached houses generally to have private, dedicated parking spots. In this situation, it is relatively easy to move large loads of groceries from the car to the house. Changing the oil in the driveway is no problem. Easy access from the house to the car almost makes it a household appliance rather than a discrete conveyance. As the number of attached units rises, this becomes less and less true. Parking areas are more likely to be shared. The distance from the car to the unit increases. Servicing the car may be forbidden in shared lots. Generally, using the car becomes harder. Following this line of argument, we should expect the benefits of vehicle availability, and vehicle availability itself, to fall as units are attached to a greater number of other units.

Whereas unit type is being introduced here as a substitute for demographic variables that cannot land in a residential parking regulation, we must consider its likely relationship with these demographic variables. First, consider household income. We can assume that space is a normal good, of which more is purchased as more spending power is acquired. Higher incomes should be associated with more private housing, all else being equal. Second, consider children. Studies cited in Chapter 2 found that households with children particularly value space (Handy et al., 2004; Waddell & Nourzad, 2002). This suggests that as the number of children rises, so does the likelihood of choosing a more private housing unit, all else being equal.

Here, unit type is operationalized as a categorical variable, using the eight categories of immobile housing available in the Decennial Census PUMS.

Bedrooms The number of bedrooms in the unit should relate to three drivers of household vehicle availability: demand for activity outside the home, preference for space, and the income constraint. We expect, all else being equal, that the number of bedrooms should tend to increase as the number of household residents increases, and that more people should mean more activity demand. As to preference for space, the relationship between residents and bedrooms, and therefore between activity demand and bedrooms, will be stronger for households with a greater preference for space. Finally, we should expect number of bedrooms to be a measure of household income, inasmuch as living space is a normal good. Taken individually and together, these three relationships suggest that number of bedrooms should be positively associated with vehicle availability, all else being equal.

Method

The task at hand is to explore the relationships among household demographics, household choices about the residential unit (unit type, bedrooms and location), and the household choice of how many vehicles to own. We approach this task using linear regression for three reasons. First, we are modeling expected values of a discrete choice averaged over all households of a large class. The ultimate output of our modeling must be a continuous, not a discrete, variable. Multiple tests of ordinal and multinomial logit modeling approaches, with the discrete output categories weighted by their probabilities, gave results indistinguishable from the results of linear models. Second, linear models are significantly easier to interpret and combine than logit or probit models. This is important especially because the present research is targeted to an audience of innovators *in practice*, who may not be well versed in discrete methods. Finally, linear models lend themselves to an omitted bias framework, which is natural for the present set of questions.

An omitted bias analysis is appropriate here: We need to understand how well a vehicle availability model performs given that it employs only residential unit choice–unit type, bedrooms and location–while ignoring household demographics. Omitted bias analysis is designed to estimate the bias in a model's coefficients due to the omission from the model of important predictors[16].

Omitted variable bias analysis includes three essential steps. First, the full equation is estimated, with no variables excluded. Second, a short regression is estimated, using only the independent variables to be used in standard-setting protocols–unit type, bedrooms and location. Third, "artificial" regressions are estimated to explicate the relationships between the excluded demographic variables and the regulation-appropriate variables.

[16]This discussion follows Imbens (2005); introductory econometrics texts such as Hill, Griffiths & Judge (2001) cover the method as well.

Results & discussion

Short regression: vehicles regressed on only residential choice. In practice we will exclude the highly influential but unknowable demographic variables, and use only the variables fixed to the housing unit. The short regression represents this situation. It allows us to examine the relationships between our available predictors and the dependent variable, assuming that we allow the demographic variables to covary with the predictors. Some of the effects of the demographic covariates are included in the regression coefficients in Table 3.7.

Table 3.7. Vehicles per household, r^2=0.250

Parameter	***B***	***Std. Err.***	***t***	***Sig.***
Intercept	.415	.022	19.226	.000
[Single family detached]	.557	.025	21.883	.000
[Single family attached]	.474	.037	12.695	.000
[2 units in struct.]	.396	.029	13.608	.000
[3-4 units in struct.]	.260	.031	8.484	.000
[5-9 units in struct.]	.328	.034	9.575	.000
[10-19 units in struct.]	.318	.034	9.369	.000
[20-49 units in struct.]	.254	.035	7.209	.000
[50+ units in struct.]	0(a)	.	.	.
[Single family detached] * BR	.299	.004	74.754	.000
[Single family attached] * BR	.241	.012	20.544	.000
[2 units in struct.] * BR	.282	.008	35.154	.000
[3-4 units in struct.] * BR	.282	.012	24.253	.000
[5-9 units in struct.] * BR	.218	.015	14.181	.000
[10-19 units in struct.] * BR	.265	.017	15.441	.000
[20-49 units in struct.] * BR	.282	.020	13.836	.000
[50+ units in struct.] * BR	.378	.017	22.011	.000
[Single family detached] * BR * density	-.028	.001	-23.322	.000
[Single family attached] * BR * density	-.051	.004	-12.547	.000
[2 units in struct.] * BR * density	-.055	.004	-14.959	.000
[3-4 units in struct.] * BR * density	-.085	.005	-16.144	.000
[5-9 units in struct.] * BR * density	-.123	.006	-19.673	.000
[10-19 units in struct.] * BR * density	-.132	.008	-17.112	.000
[20-49 units in struct.] * BR * density	-.129	.010	-12.548	.000
[50+ units in struct.] * BR * density	-.082	.009	-9.134	.000

a This parameter is set to zero because it is redundant.

The model results in Table 3.7 conform to the predictions enunciated above. First, controlling for bedrooms and location, vehicle availability generally decreases as the number of attached units increases[17]. Single-family detached units have more vehicles than single-family attached units, which have more than all other attached units[18]. Units in 50 or more-unit structures have fewer vehicles available than units in any other unit type.

This is consistent with the predictions made above. Controlling bedrooms roughly controls for activity demand and income variations, assuming that bedrooms are associated with household size and income. (This is confirmed below.) Controlling PUMA density roughly controls for land use variations and the associated differences in the relative utility of owning and using autos[19]. That leaves differences in parking supply, or ease of accessing parking from the unit, associated uniquely with unit type. Of course, the effects here include the effect of influential covariates that this analysis neglects, such as household income and number of workers. These covariates are likely responsible for a substantial portion of the effect that this analysis ascribes to unit type.

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[17]We use a t test to compare the estimates of the regression equation coefficients. If we assume that the regression errors are normally distributed, then the coefficients are normally distributed. The t-statistic is the difference in the coefficients divided by the standard error of that difference. The standard error of the difference is roughly the square root of the sum of the squared standard errors (Miller, 2006a:243). The degrees of freedom for the t-statistic is of the same order as the degrees of freedom for either regression coefficient. The model has 27 degrees of freedom while the PUMS sample has over 115,000 observations in it, and therefore roughly 115,000 degrees of freedom. The critical t-statistic value for a two-tailed t-test at α=0.05 for DF>120 is less than 1.98. We assume that regression coefficients b_1 and b_2 differ significantly where $t = b_1 - b_2 / (se_{b1}^2 + se_{b2}^2)^{0.5}$ exceeds 1.98. Unless otherwise noted, where the text refers to a difference in regression coefficients it is a statistically significant difference.

[18]The difference between single-family detached and single-family attached units' vehicle availability is marginally significant, $p<0.1$. The same is true for the difference between single-family attached units and those in 2-unit structures. Single-family detached units have more vehicles than all multifamily units, $p<0.05$.

[19]A caveat here is that PUMAs are large enough to encompass wide density variations within their borders. Given that multifamily housing is more common in denser areas, the effects associated with unit type here may also reflect local land use effects.

A second way in which the results conform to predictions is in the association between bedrooms and vehicles available. Bedrooms are taken to be associated with the number of household residents, their preference for space, and their income. As such, we expect bedrooms to be positively associated with vehicles. That is the case in this analysis, across all unit types, and at all densities. The normalized PUMA densities in the sample range from about -2 to 2, whereas the coefficients on [unit type] * BR have more than double the magnitude of the coefficients on [unit type] * BR * density for all unit types. As a result, the model suggests that increasing bedrooms increases vehicles for all households in the sample[20].

A third predicted finding is that increasing density reduces household vehicle availability, controlling for bedrooms and unit type. Density is taken here as a proxy for the difficulty of using autos, the ease of accessing jobs by alternative means, and the ease of accessing staple (pedestrian-oriented) services such as convenience stores and dry cleaners. Across all unit types, controlling for bedrooms, increased density is associated with reduced auto ownership.

It bears repeating that these associations have at least two parts. One is the indirect effect of important demographic variables that covary with the residence choice variables used as predictors in this model. For example, increasing bedrooms are presumed to be associated with increasing household size—a driver of activity demand—and income (this association is confirmed in a subsequent section). Part of the association between bedrooms and vehicles is due to these links, and the links between activity demand and income and vehicle availability. A second part of the total effect

[20]Units in 5- to 9-unit structures are an exception. However, the total bedroom effect at density=2 is not significantly different from zero, at p=0.05.
$[0.218 + 2*(-0.123) =]\ -0.028.\ \ |-0.028| = 0.028 < 0.032\ [= 1.98*(0.015^2+0.006^2)]$.

could be termed a direct effect, but in this case we use the term to refer to effects that are not otherwise captured. The choice of bedrooms has absolutely no direct causal relationship to vehicle availability. However, it may reflect an attitude, such as a preference for space or privacy, that does factor more directly in the choice of how many autos to own.

Our next step is to investigate the indirect effects of bedrooms, unit type and density, by considering their demographic covariates.

Artificial regressions: demographics on residential choice. As mentioned above, the regression coefficient differences between the full regression and the short regression are driven by the covariation of the predictors—unit type, bedrooms and location—and the excluded demographic variables. The task remains to quantify that covariation in order to analyze the biases introduced by omitting the demographic variables. The following artificial regressions, with the excluded variables regressed on the predictors, accomplish that task.

Table 3.8. Workers per household, r^2=0.080.

Parameter	***B***	***Std. Error***	***t***	***Sig.***
Intercept	.350	.023	15.039	.000
[Single family detached]	.254	.028	9.219	.000
[Single family attached]	.247	.040	6.136	.000
[2 units in struct.]	.470	.031	14.988	.000
[3-4 units in struct.]	.451	.033	13.601	.000
[5-9 units in struct.]	.479	.037	12.966	.000
[10-19 units in struct.]	.400	.037	10.929	.000
[20-49 units in struct.]	.383	.038	10.081	.000
[50+ units in struct.]	0(a)	.	.	.
[Single family detached] * BR	.249	.004	57.732	.000
[Single family attached] * BR	.265	.013	20.955	.000
[2 units in struct.] * BR	.208	.009	24.030	.000
[3-4 units in struct.] * BR	.200	.013	15.933	.000
[5-9 units in struct.] * BR	.179	.017	10.768	.000
[10-19 units in struct.] * BR	.242	.019	13.066	.000
[20-49 units in struct.] * BR	.226	.022	10.268	.000
[50+ units in struct.] * BR	.286	.019	15.433	.000
[Single family detached] * BR * density	.000	.001	-.205	.837
[Single family attached] * BR * density	.014	.004	3.281	.001
[2 units in struct.] * BR * density	-.009	.004	-2.199	.028
[3-4 units in struct.] * BR * density	.004	.006	.665	.506
[5-9 units in struct.] * BR * density	-.002	.007	-.351	.726
[10-19 units in struct.] * BR * density	-.014	.008	-1.671	.095
[20-49 units in struct.] * BR * density	-.021	.011	-1.849	.065
[50+ units in struct.] * BR * density	.029	.010	3.028	.002

a This parameter is set to zero because it is redundant.

The number of workers per household generally follows expectations. First, across unit type, workers per household increases with increasing bedrooms. This is consistent with the idea that adding household members increases the demand for space.

Second, for single-family attached units and those in structures with more than 50 units, higher densities are associated with more workers per bedroom. This effect is intuitive: where densities are higher and land is presumably more valuable, workers are more crowded into bedrooms. However, most unit types show insignificant sensitivity of workers per bedroom to density; units in 2-unit structures show the opposite behavior. That is, they hold fewer workers per bedroom in denser PUMAs; conversely, households who choose 2-unit structures in denser PUMAs choose more bedrooms per worker than do their low-density counterparts. Assuming that bedrooms are a normal good, this suggests that residents of 2-unit structures in urban environments may hold a greater income advantage over their low-density counterparts than do urban residents of single-family attached houses (where crowding results from higher densities).

Table 3.9. Nonworking adults per household, r^2=0.026

Parameter	***B***	***Std. Error***	***t***	***Sig.***
Intercept	.732	.021	35.521	.000
[Single family detached]	.060	.024	2.473	.013
[Single family attached]	-.082	.036	-2.311	.021
[2 units in struct.]	-.134	.028	-4.815	.000
[3-4 units in struct.]	-.276	.029	-9.425	.000
[5-9 units in struct.]	-.210	.033	-6.429	.000
[10-19 units in struct.]	-.226	.032	-6.965	.000
[20-49 units in struct.]	-.204	.034	-6.062	.000
[50+ units in struct.]	0(a)	.	.	.
[Single family detached] * BR	.016	.004	4.125	.000
[Single family attached] * BR	.049	.011	4.356	.000
[2 units in struct.] * BR	.097	.008	12.707	.000
[3-4 units in struct.] * BR	.153	.011	13.810	.000
[5-9 units in struct.] * BR	.073	.015	4.972	.000
[10-19 units in struct.] * BR	.045	.016	2.773	.006
[20-49 units in struct.] * BR	.060	.019	3.107	.002
[50+ units in struct.] * BR	.032	.016	1.945	.052
[Single family detached] * BR * density	.024	.001	20.811	.000
[Single family attached] * BR * density	.042	.004	10.792	.000
[2 units in struct.] * BR * density	.057	.003	16.450	.000
[3-4 units in struct.] * BR * density	.057	.005	11.279	.000
[5-9 units in struct.] * BR * density	.090	.006	15.050	.000
[10-19 units in struct.] * BR * density	.082	.007	11.076	.000
[20-49 units in struct.] * BR * density	.074	.010	7.507	.000
[50+ units in struct.] * BR * density	.001	.009	.161	.872

a This parameter is set to zero because it is redundant.

Table 3.9 indicates that unit type, bedrooms and PUMA density explain only 2.6% of the household variation in the number of nonworking adults. The lower fit may be attributable to the variety of lifestyles that compose the category of nonworking adults. They should be mostly retirees and nonworking spouses. The group would also include disabled adults living in households, rather than group quarters.

Despite the poor fit, the model shows a few statistically significant relationships. First, for all unit types, number of nonworking adults is positively associated with number of bedrooms; units with more bedrooms tend to house more nonworking adults. (This is only marginally true for units in 50 or more-unit structures.) This is consistent with the theory that marginal household members demand marginal living space.

Second, the interaction of bedrooms and density is positively associated with nonworking adults. That is, at higher densities there are more non-working adults per bedroom (except in 50 or more-unit structures). Higher densities and presumably higher land costs and costs per bedroom lead to crowding.

Finally, nonworking adults command less living space than do working adults. Across all levels of unit type, the values of the coefficients on bedrooms are significantly greater in Table 3.8 than in Table 3.9. On average, working adults hold more bedrooms than do nonworking adults.

Table 3.10. Children per household; r^2=0.067

Parameter	***B***	***Std. Error***	***t***	***Sig.***
Intercept	-.097	.023	-4.139	.000
[Single family detached]	-.024	.028	-.875	.382
[Single family attached]	.056	.040	1.376	.169
[2 units in struct.]	.392	.032	12.452	.000
[3-4 units in struct.]	.221	.033	6.647	.000
[5-9 units in struct.]	.143	.037	3.860	.000
[10-19 units in struct.]	.114	.037	3.113	.002
[20-49 units in struct.]	.107	.038	2.792	.005
[50+ units in struct.]	0(a)	.	.	.
[Single family detached] * BR	.246	.004	56.901	.000
[Single family attached] * BR	.251	.013	19.773	.000
[2 units in struct.] * BR	.129	.009	14.894	.000
[3-4 units in struct.] * BR	.218	.013	17.272	.000
[5-9 units in struct.] * BR	.270	.017	16.209	.000
[10-19 units in struct.] * BR	.281	.019	15.081	.000
[20-49 units in struct.] * BR	.259	.022	11.738	.000
[50+ units in struct.] * BR	.254	.019	13.632	.000
[Single family detached] * BR * density	-.009	.001	-6.983	.000
[Single family attached] * BR * density	.032	.004	7.404	.000
[2 units in struct.] * BR * density	.030	.004	7.616	.000
[3-4 units in struct.] * BR * density	.044	.006	7.769	.000
[5-9 units in struct.] * BR * density	.054	.007	7.997	.000
[10-19 units in struct.] * BR * density	.054	.008	6.481	.000
[20-49 units in struct.] * BR * density	.051	.011	4.542	.000
[50+ units in struct.] * BR * density	.043	.010	4.358	.000

a This parameter is set to zero because it is redundant.

Table 3.10 confirms a few intuitive trends. First, number of children per household increases with increasing bedrooms, for all unit types. On average, children consume some amount of living space.

Second, children per bedroom increases with PUMA density for nearly all unit types. For all but single-family detached units, increased development densities are associated with more crowded living conditions for children. In detached units, children per bedroom is higher in less dense areas. This suggests that as density increases, the number of children per detached housing unit falls faster than the number of bedrooms per housing unit. This is consistent with the finding from the literature that households with children are particularly desirous of space–children are less common in denser areas.

Finally, controlling for density and bedrooms, units in 50 or more-unit structures have fewer children than any other unit type except single-family detached housing. Setting aside the exception, this is again consistent with the finding that households with children particularly desire space, as multifamily housing is more common in denser areas. On its face the rough equivalence of detached units and units in large multifamily buildings seems to contradict the common wisdom that detached units have significantly more children than do attached units.

However, detached units do indeed tend to have significantly more bedrooms than do attached units. In the New Jersey sample used here, in the PUMA of average density, detached units average 3.279 bedrooms whereas households in 50 or more-unit structures average 1.178 bedrooms. In concert with Table 3.10, these numbers suggest that, in a PUMA of average density, a single-family detached household will host [-0.097 + (-0.024) + (0.246) * (3.279 bedrooms) =] 0.69 children. Calculations using the same method indicate that households in 50 or more-unit structures average only 0.2 children.

Table 3.11. Natural logarithm of household income; r^2=0.208

Parameter	***B***	***Std. Error***	***t***	***Sig.***
Intercept	9.646	.021	454.365	.000
[Single family detached]	.380	.025	15.185	.000
[Single family attached]	.718	.037	19.585	.000
[2 units in struct.]	.518	.029	18.105	.000
[3-4 units in struct.]	.485	.030	16.058	.000
[5-9 units in struct.]	.550	.034	16.343	.000
[10-19 units in struct.]	.438	.033	13.130	.000
[20-49 units in struct.]	.357	.035	10.308	.000
[50+ units in struct.]	0(a)	.	.	.
[Single family detached] * BR	.342	.004	87.066	.000
[Single family attached] * BR	.198	.012	17.134	.000
[2 units in struct.] * BR	.192	.008	24.335	.000
[3-4 units in struct.] * BR	.170	.011	14.880	.000
[5-9 units in struct.] * BR	.162	.015	10.690	.000
[10-19 units in struct.] * BR	.248	.017	14.687	.000
[20-49 units in struct.] * BR	.281	.020	14.012	.000
[50+ units in struct.] * BR	.443	.017	26.273	.000
[Single family detached] * BR * density	-.007	.001	-5.501	.000
[Single family attached] * BR * density	-.025	.004	-6.322	.000
[2 units in struct.] * BR * density	-.012	.004	-3.321	.001
[3-4 units in struct.] * BR * density	-.026	.005	-5.049	.000
[5-9 units in struct.] * BR * density	-.076	.006	-12.440	.000
[10-19 units in struct.] * BR * density	-.089	.008	-11.700	.000
[20-49 units in struct.] * BR * density	-.077	.010	-7.603	.000
[50+ units in struct.] * BR * density	-.011	.009	-1.197	.231

a This parameter is set to zero because it is redundant.

Table 3.11 describes the relationship between the logarithm of household income and the regulation-appropriate variables, and permits a few observations. First, the intuitive result: increasing bedrooms is associated with increasing income for all unit types. Bedrooms are indeed normal goods.

Second, income is less sensitive to bedrooms at higher densities for all unit types except 50 or more-unit structures. This is indicated by the statistically significant coefficients of opposite sign for bedrooms and the product of bedrooms and density, for nearly all unit types. Conversely, bedrooms are a better proxy for income in low density PUMAs than in high density PUMAs for nearly all unit types.

This implies that urban household incomes are less driven by space than are rural incomes. Let us assume that the housing unit value is characterized in terms of space and accessibility, as described in Chapter 2, and that bedrooms are a decent measure of household space (while holding unit type constant). Then to the extent that spaciousness drives urban household incomes less than it does rural incomes, it follows that accessibility affects urban incomes more, in relative terms. If we further assume that housing values are correlated with incomes, this suggests that location-related amenities play more of a role in determining housing value in urban locations than in rural ones. This is intuitive, as greater variety in land use coupled with greater potential proximity should intensify the value increment associated with nearby uses.

This section's analysis of the relationship between household sociodemographics and residential unit characteristics provides a basis for using the latter in determining household vehicle availability. The sociodemographic variables vary with unit type, bedrooms and location in ways that are consistent with theory and previous studies. Building on these explorations, the final step here is to analyze the relationship between residential unit characteristics and vehicle availability while controlling for the sociodemographic covariates.

Full regression: vehicles regressed on residential choice and demographics. This step is to estimate the influence of each variable of interest while controlling for covariates that are impractical to measure. It provides our best estimate of the relationships between the predictors and the dependent variable, vehicles. This is the benchmark against which the short regression results are compared.

Table 3.12. Vehicles per household; r^2=0.440

Parameter	***B***	***Std. Error***	***t***
Intercept	-1.746	.033	-52.790
[Single family detached]	.363	.022	16.481
[Single family attached]	.250	.032	7.741
[2 units in struct.]	.135	.025	5.355
[3-4 units in struct.]	.041	.027	1.547
[5-9 units in struct.]	.068	.030	2.286
[10-19 units in struct.]	.115	.029	3.934
[20-49 units in struct.]	.069	.030	2.277
[50+ units in struct.]	0(a)	.	.
[Single family detached] * BR	.130	.004	35.750
[Single family attached] * BR	.086	.010	8.427
[2 units in struct.] * BR	.139	.007	19.882
[3-4 units in struct.] * BR	.137	.010	13.511
[5-9 units in struct.] * BR	.102	.013	7.641
[10-19 units in struct.] * BR	.112	.015	7.498
[20-49 units in struct.] * BR	.125	.018	7.100
[50+ units in struct.] * BR	.170	.015	11.442
[Single family detached] * BR * density	-.032	.001	-30.769
[Single family attached] * BR * density	-.060	.003	-17.212
[2 units in struct.] * BR * density	-.060	.003	-19.095
[3-4 units in struct.] * BR * density	-.093	.005	-20.374
[5-9 units in struct.] * BR * density	-.125	.005	-23.169
[10-19 units in struct.] * BR * density	-.126	.007	-18.789
[20-49 units in struct.] * BR * density	-.120	.009	-13.532
[50+ units in struct.] * BR * density	-.092	.008	-11.821
Working adults	.424	.003	144.069
Nonworking adults	.216	.003	70.814
Children	-.024	.002	-9.975
Household income (natural log)	.192	.003	67.044

a This parameter is set to zero because it is redundant.

Table 3.12 summarizes the model, which explains 44% of the variance in household vehicle availability. Controlling for bedrooms, location and demographics, unit type is significant. Single-family detached housing units have significantly more vehicles associated with them than do single-family attached units. Single-family attached units have significantly more vehicles than do all other forms of attached housing. Except for the 3-4 family group, all unit-type levels have significantly higher vehicle availability than do residences in structures with 50 or more units. All else being equal, increasing the number of attached units generally reduces vehicle availability.

This is consistent with the discussion of variables above. The effect may be related to the ease of access to nearby parking, whether off-street or not, as proposed above. It may also be related to the fact that multi-family housing is more common in denser areas. Our spatial unit, the PUMA, admits significant density variation within its borders, and multifamily housing should tend to be located in the denser parts of PUMAs. Therefore, the unit-type associations may be partly attributable to intra-PUMA density variations.

Across all levels of unit type, increasing density decreases the number of vehicles available per bedroom in the unit. Vehicles per bedroom is less sensitive to density for single-family detached units than for all attached housing types. For single-family attached units and those in 2-unit buildings, vehicles per bedroom is less sensitive to density than it is for units in larger buildings.

Overall, the fact that increasing PUMA density is associated with decreasing vehicles per bedroom is consistent with expectations. The construction of the model shows that, controlling for unit type, bedrooms and demographics, increasing density decreases vehicle availability. In this analysis, PUMA density stands as a proxy for the difficulty in automobile use due to road network loading, job accessibility which facilitates work travel by non-automotive means, and land use mix which brings more pedestrian-oriented businesses closer to residences. Individually and together, these three effects should reduce the relative benefit of household vehicle availability and the chosen level thereof. This analysis is consistent with that expectation.

Further, the fact that single family detached units show the least sensitivity to density, controlling for all other variables, is also consistent with the predictions presented above. Unit type is described here and elsewhere as being associated with the supply of parking, or the ease of accessing parking (Chu, 2002). Density interacts with unit type in proxying parking supply: for single-family detached houses, increased density reduces the likelihood of having dedicated off-street parking available. Regardless of density, parking for multi-family housing tends to be in shared lots. For these units, increasing development density leads to increased building heights, which increases the difficulty of accessing parking from the home. Increased density is also associated with increased monetary cost of providing parking: land tends to be more expensive, which tends to lead to reductions in surface parking and the possibility of structured parking, which is both more expensive to provide and less pleasant to use, generally, than surface parking. Further, all else being equal, as development density increases, the demand for on-street parking increases, as there are more building users per linear foot of roadway. Therefore, on-street parking becomes more costly to use, either in monetary terms or in terms of search time.

The demographic control variables have influences on vehicle availability that comport with predictions as well. The number of working adults is positively associated with vehicle availability, with greater impact and statistical significance than nonworking adults. This is consistent with the ideas proposed above that greater numbers of adults lead to greater travel demand, and that workers induce greater household travel demand than do nonworkers. The number of children has a weakly negative association with vehicle availability. Although the coefficient is statistically significant, the impact of children is almost negligible: all else being equal, the model suggests that a household with four children averages about 0.1 vehicles fewer than a zero-child household. Finally, as predicted, increasing household income is associated with increasing vehicle availability.

Conclusions

Overall, the residential choice variables capture some but not much of the variance in the key demographic variables, all of which are positively correlated with bedrooms at a given level of unit type. This is consistent with the fact that the regression coefficients on unit type and its interaction with bedrooms are greater when demographics are excluded, as discussed above in the comparison of Table 3.12 and Table 3.7. In the short regression (Table 3.7), the coefficients on our regulation-appropriate predictors include the effects of the covarying demographic predictors, whereas the coefficients in the full regression (Table 3.12) do not. Tables 3.8 through 3.11 indicate that an increase in bedrooms is associated with increases in all the demographic covariates. Table 3.12 indicates that household vehicle availability is positively associated with the demographic covariates (except children, which has an insubstantial association with vehicles) when controlling for bedrooms. Taken together, these facts explain that as bedrooms increases, household vehicle availability tends to increase by the direct effect of bedrooms plus the indirect effect created by bedrooms' association with the demographic covariates. The long regression's coefficients shows the direct effect of bedrooms whereas the short regression's coefficients show the sum of the direct and indirect effects.

Selecting a geographic scale

At this point we have concluded that the method being developed to estimate parking standards should rely on unit type, bedrooms and location of a housing unit to be regulated. But the location variable must be defined to be useful. This chapter includes analyses of the impact of location conducted at the PUMA and Census tract level. It also refers to existing residential parking standard regimes that consider a unit's location variously as its state, region, county, city or urban neighborhood of residence. In preparing to specify and evaluate a method for establishing residential parking standards, we must consider the question of what geographic unit is most appropriate.

Our task is to project average household vehicle availability for a new residential development. We know that vehicle availability is determined primarily by household demographic characteristics and secondarily by location-related differences in the relative utility of vehicle ownership. We know that the relationship between demographic characteristics and residential unit choice is moderated by location-related factors, a major one being local real estate prices. These are in turn determined by access to local amenities and disamenities such as a lake view or train tracks.

The question then is what is the best geographic unit to use so as to be able to accurately infer the value of local amenities and their impact on average household vehicle availability. This of course raises the question of the transience of local amenities and the challenge of predicting future values of anything. This does not mean, however, that we must limit ourselves to evaluating only the land-use/transportation related impacts of roads, transit and various types of development. These features are clearly long-lived, and should be expected to endure at least one cycle of revaluation and devaluation. However, I would argue that such cycles are relatively slow. By and large, homebuyers seek out neighbors of similar means. As a result, local home values tend to be relatively stable in their relationship to the regional mean. It is therefore meaningful and appropriate to estimate geographical housing market variations, and include these impacts in our location-based estimates of average household vehicle availability[21].

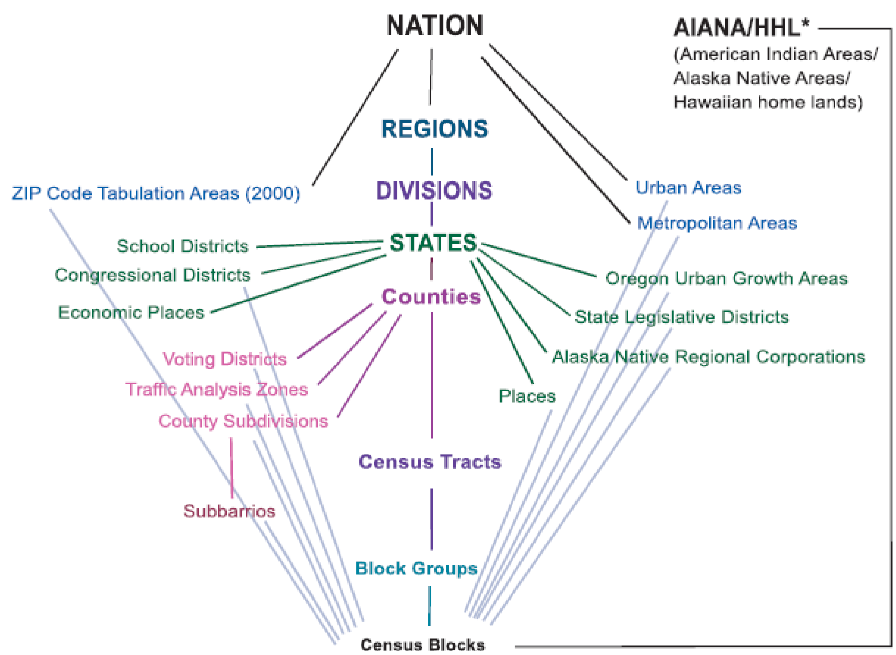

Figure 3.1. Geographic units in the U.S. Decennial Census
(Source: http://www.census.gov/geo/www/geodiagram.pdf)

[21]No doubt that some new developments are large enough to effectively create their own neighborhood context. In such cases the projections resulting from any backward-looking modeling approach should be treated with suspicion. If possible, those projections should be corrected for differences in income. Such a correction is possible using the equations derived in Chapter 4.

Figure 3.1 diagrams the various geographic units that the U.S. Census Bureau uses to report tabular results. Although other data sources may use different geographies, the Census Bureau's system is undoubtably the most comprehensive, and many private data collection projects use Census units or variations thereof (Renne, 2005; Parsons Brinckerhoff Quade and Douglas, 2005a). It is a natural place for us to start the discussion of appropriate geographic units.

Table 3.13. Characteristics of geographic units in New Jersey

Unit	***Number***	***Census-defined population (residents)***	***Average population in New Jersey (residents)***	***Average area in New Jersey (mi^2)***	***Distance scale* (mi)***
County	21	not defined	400,683	353.19	10.60
PUMA	61	>100,000	137,940	121.59	6.22
Tract	1950	4,000 (design target)	4,315	3.80	1.10
Block group	6510	1,500 (design target)	1,293	1.14	0.60
Block	141,342	not defined	59	0.05	0.13

*Distance scale is the radius of a circle with the given area.
Source: US Census Bureau, http://www.census.gov

Table 3.13 shows a sample of our options that are smaller than a state–the largest jurisdictional level at which land use is regulated. Counties are defined politically, whereas the block is defined by the street network; the other three options have the advantage of being systematically defined by the Census Bureau. PUMA is included here, although it is missing from Figure 3.1, because household data are reported at this level which allows tabulations to be computed.

Table 3.14. Density and size of New Jersey's Census tracts and block groups

	Land area (mi^2)		***Population density (persons/mi^2)***	
	Tract	Block group	Tract	Block group
Minimum	0.02	.004	.00	.00
25th percentile	.40	.10	1528	2034
50th percentile	1.01	.23	3826	4722
75th percentile	2.69	.61	9276	10545
Maximum	100.14	100.14	114588	136385

Before moving forward with a statistical test, we should compare the sizes of Census tracts and block groups to the smallest geographic scales at which vehicle availability relationships differ. Table 3.14 indicates Census block group and tract sizes in New Jersey, by quartile. In the places where it matters most, the densest 25% of the state, Census tracts are 0.4 square miles or less. Assuming a circular tract, this equates to a radius of 0.36 miles, less than the 0.5-mile metric used by many to delineate the impact of a rail station, representative of a typical maximum walking distance (Renne, 2005). This suggests that for the densest quarter of the state the tracts are small enough to capture the smallest direct locational effect on household vehicle availability—pedestrian-scale effects.

However, Tables 3.8 through 3.11 remind us that location also relates to vehicle availability through household demographics. Outside of large housing developments, average home values can differ dramatically over less than a half mile, indicating that the vehicles/unit-choice relationship can as well (see Table 3.12).

Theoretical considerations

Given these options, what unit is best? This question is related to the modifiable areal unit problem, one that Fotheringham and colleagues (Fotheringham, Brundson, & Charlton, 2000) cite as a current challenge in quantitative geography. The issue is that spatial regressions often give different results depending on the way that the data are aggregated. Generally, larger areal units are associated with higher r^2 for models that seek to explain variation among the units. Also, the zoning system—the particular boundary network—can influence the results. Fotheringham et al. present a range of proposals for choosing the ideal areal unit, but find no consensus.

Babbie (2000) provides more general guidance on the quality of measurement. First, to be useful, a measurement should be valid—it should be related conceptually to the question of interest in the asserted manner. Second, it should be reliable. Its result should not depend on the method or timing of data collection. Third, it should be precise; it should be developed with minimum uncertainty. Fourth, it should be accurate rather than incorporating any persistent bias.

The questions of validity and reliability can be answered relatively quickly. The data and data reduction methods used here are valid to the extent that they can be used to predict household vehicle availability for housing units yet to be built. Most of the foregoing discussion in this chapter and in Chapter 2 revolves around the most valid way to conceive of the determinants of residential parking demand. The only further point to make here is that we do assume that existing relationships between vehicle availability and residential unit choice (bedrooms, unit type and location) describe future patterns in newly constructed housing units. The data are reliable to the extent that respondents can and will consistently provide the survey data requested. The method's reliability rests on a consistent relationship between the data and the projections derived therefrom.

The methods presented here are precise to the extent that they estimate household vehicle availability, given bedrooms, unit type and location, with low uncertainty. This is largely a question of data availability. All else being equal, a larger sample with more measurements in each combination of levels of independent variables gives a lower standard error of the estimate, which is a typical measure of model uncertainty. The demand for precision is a call for larger samples.

In contrast, to achieve accuracy and avoid bias we must use as small an areal unit as possible, as it is assumed that locational effects are uniform in each areal unit of analysis. When aggregation areas are larger than the scale of locational effects, relationships computed within the areas are biased toward the global average. Consider the example of a small city with a lake that has residential development on its shore. That lakeshore development will tend to be more expensive than housing without a view. Its residents will tend to have higher incomes, controlling for bedrooms and unit type, than elsewhere in the city. Given that higher incomes correlate with higher vehicle availability (again controlling for bedrooms and unit type), residents of lakeshore properties are likely to have more vehicles per bedroom than similarly housed residents of other parts of the city. If the entire city is used as the areal unit of analysis, this difference is averaged away. Accuracy demands small areal units.

The tension between the need for large samples, for precision's sake, and the need for small areal units generally cannot be resolved simply by spending more on sampling. Resources are generally unavailable for such intensive sampling. Given this research's aim of developing a method that can be used by regulators throughout the US, a way to evaluate the trade-off between sample size and areal unit size in existing publicly available data sets must be developed.

Ideally, the question of how small to make the areal unit would be answered with a statistical test. We would effectively compare two regression models on a cost-benefit basis. How certainly can we say that the additional error reduction offered by the model using smaller areal units (and therefore effectively more regression coefficients) is worth the cost of losing degrees of freedom? An F-test is commonly used to answer this question (Hill et al., 2001).

Data

The data to compare useful areal units in this way are not publicly available. The Decennial Census PUMS offers household-level data with households located to the 100,000 or more-person PUMA. The 2000 Census Transportation Planning Package includes numerous cross-tabulations involving vehicle availability at the tract and block group levels, but it lacks bedroom data. Other public data sources were also considered–the National Household Travel Survey, the American Housing Survey, and the American Community Survey–but they locate survey respondents in areas too large for our purposes. The Regional Travel-Household Interview Survey conducted by MPOs in northern New Jersey and New York City, which locates responding households to their Census tract, also lacks bedroom data (Parsons Brinckerhoff Quade and Douglas, 2005a).

Therefore, it was necessary to purchase a custom tabulation from the Census Bureau. The purchased sample includes data from all block groups in New Jersey that held at least 50 households that responded to the long-form survey. This is roughly equivalent to requiring at least 300 households be present in the block group. Of New Jersey's 6,445 block groups with at least one household, the sample includes 3,900.

For each block group that met the threshold, the distribution of households by unit type, bedrooms and vehicles available is reported. Unit type includes single-family detached, single-family attached, units in two- to four-unit structures, and units in structures with five or more units. These are also the levels reported in the Census Transportation Planning Package (CTPP). Bedrooms and vehicles available are reported in five levels: from zero to four or more. Following standard Census practice to protect confidentiality, cell totals above eight are rounded to the nearest multiple of five.

For this comparison, it was necessary to identify the block groups that compose complete tracts. Of the 3,900 block groups in the sample, 1,719 block groups compose 729 complete tracts. These 729 tracts represent 37.6% of the 1,938 tracts in New Jersey containing households, and 36.0% of all the housing units in New Jersey. Table 3.15 compares the sample to the state on the basis of tract housing density.

Table 3.15. Density comparison: sample versus entire State of New Jersey

	Housing density (units/mi^2)		***Logarithm of housing density***	
	Sample	NJ	Sample	NJ
Mean	3,424	3,148	7.04	7.15
Standard deviation	5,810	4,553	1.60	1.58
N	729	1,938	729	1,938

One-sample t tests indicate that housing density in the sample tracts does not differ significantly from the set of all tracts in New Jersey ($p=0.217$), whereas the natural logarithm of housing density does differ ($p<0.05$). The sample has a lower average logarithm of housing density—the functional form used earlier in the chapter—than does the set of all tracts in the state.

Method

The overall approach here is to use an F test to determine whether measuring average household vehicle availability at the block group level, rather than the tract level, improves our estimates of vehicle availability in a statistically significant way. An F test is used to compare a restricted model against an unrestricted model. Often, the unrestricted model is a regression equation with a number of coefficients, while the restricted model requires that some of those coefficients are zero. The application is slightly different here, but the principle is the same. (This discussion is drawn from Hill et al., 2001.)

An F distribution is generated when two χ^2-distributed variables, with degrees of freedom m_1 and m_2, are divided by their degrees of freedom and then one such ratio is divided by the other. That is, if V_1 is χ^2-distributed with m_1 degrees of freedom and V_2 is χ^2-distributed with m_2 degrees of freedom, then $(V_1/m_1)/(V_2/m_2)$ is F distributed with (m_1, m_2) degrees of freedom. A χ^2 distribution is generated when a series of independent normally distributed variables are squared and summed. Therefore, the applicability of an F test relies principally on the normality of the fundamental distributions.

The distributions in this case are no less normal than in a case wherein two regression equations, one of which is a restricted version of the other, are being compared. An F test compares the F statistic to a critical value which depends on the degrees of freedom. The F statistic is computed as $[(SSE_R - SSE_U)/(K_U - K_R)]/[(SSE_U/(T - K_U)]$, where SSE_R is the sum of squared errors (SSE) for the restricted model, SSE_U is the SSE for the unrestricted model, K_R is the number of nonzero coefficients in the restricted model, K_U is the number of nonzero coefficients in the unrestricted model, and T is the number of observations. The SSE terms are taken to be χ^2-distributed, as they are given by the sum over all observations of $(y - \hat{y})^2$, where y is the observed value and $\hat{y}$ is the predicted value. Therefore, $(y - \hat{y})$, the model error, is taken to be normally distributed. This is no worse an assumption when the two models being compared are roughly independent, the case here, than when one is a restricted version of the other.

We implement the F test with the following steps. First, for every block group in the study area, the block-group average household vehicle availability is computed for all combinations of unit type and bedrooms. These are the model predictions for all households in the unit type/bedrooms cells in the given block group. The SSE for each household in the block group is computed, and then summed. Second, this process is repeated using the tract-average household vehicle availability for all combinations of unit type and bedrooms. The tract-average vehicle availabilities by unit type and bedrooms are used as the model predictions in the computation of the SSE. This is again summed over all households. Third, the F statistic described above is computed. The model with block group-level averaging gives us SSE_{BG} and K_{BG}, and the tract-level averaging gives us SSE_{TR} and K_{TR}.

Results & discussion

Table 3.16 shows that household vehicle availability, controlling for bedroom and unit type, is statistically significantly better estimated using block group-level averages rather than tract-level averages. The sample used here contains 1,719 block groups that compose 729 complete tracts. The number of coefficients in each model is the number of unit type x bedrooms x areal unit cells that contain households. Each of these cells has a computed average household vehicle availability, and these averages constitute the models. If every cell in the sample contained households, the block group-level model would contain 1,719 x 4 (levels of unit type) x 5 (levels of bedrooms) = 34,380 averages. Because some cells contain no households, K_{BG} in Table 3.16 (15,611) is less than this number (34,380). One-sixth of the number of households in the study area is used as T, with this ratio coming from the sampling design for the Census long form. Properly estimating the degrees of freedom in this way leads to a computed F of 1.50. Given the degrees of freedom listed in Table 3.16 , this is significant at $p<0.01$.

Table 3.16. F test comparing vehicle averages at tract or block group

Number of block groups	1,719	Number of tracts	729
K_{BG}	15,611	K_{TR}	8,992
SSE_{BG}	580,220	SSE_{TR}	615,299
		Number of households	1,077,453
		T	179,576
		DOF_numerator = $K_{BG} - K_{TR}$	6,619
		DOF_denominator = $T - K_{BG}$	163,964
		$F = [(SSE_{TR} - SSE_{BG})/(K_{BG} - K_{TR})]/[(SSE_{BG}/(T - K_{BG})]$	1.50

Conclusions

This chapter addresses the issue of how to characterize a given household for the purpose of setting a practical parking standard. What are the best descriptors to use? How are they related to household vehicle availability? And how should they be defined? These are among the last questions to answer before proposing a method for estimating household vehicle availability, and they must be answered in terms of our criteria for practicality. In short, bedrooms, unit type and location must be used in a data-driven residential parking regulation scheme.

They respect criterion #3 from above: the method must be married to the decision process. Bedrooms, unit type and location are fixed characteristics of a housing unit, as opposed to changeable demographic characteristics of occupants. Regulators can readily recognize these unit characteristics without considering demographic trends, relying on contractual arrangements or using a tape measure. The review of existing residential parking standards indicates that they are currently in wide use, which shows that the current participants in the regulation process are able to use them.

The parking standard review also provides evidence that this choice of descriptors respects criterion #2: the method must be scientifically sound. Combined with the literature review in Chapter 2, the review indicates that bedrooms, unit type and location are sufficient, in the sense that no additional influential variables are appropriate for inclusion in the method. Furthermore, the second section of this chapter demonstrates that all three variables are necessary in the method. Bedrooms, unit type and location relate to household vehicle availability independently and in concert, and the effects are substantial. Excluding any of the three would needlessly average away substantial variations. Bedrooms, unit type and location are necessary and sufficient housing unit descriptors.

The third section explores the relationships among our regulation appropriate variables, influential demographic drivers of vehicle availability, and household vehicle availability itself. It provides the rationale for using bedrooms, unit type and location in the method under development, in terms of these variables' associations with important demographic variables and in terms of their direct effects. It shows that the three descriptors have a consistent and predictable relationship with household vehicle availability—this is an essential element of being scientifically sound.

The fourth section completes the development of scientifically sound descriptors. It shows that the best areal unit with which to define household location is the Census block group (assuming a perfect estimation method). Working at the block group offers statistically significant improvement in estimating household vehicle availability from areal averages relative to the next larger unit, the Census tract. This is consistent with our suspicion that housing markets–prices for given units and the people willing to pay them–can vary dramatically from one block group to another. The Census block group is the most scientifically sound choice for areal unit, given the units and data available to decision makers: it conforms to practicality criteria #2 and #3.

Two of the three practicality criteria are met. As criterion #1, regarding the inductive basis of the method, does not apply (yet), this chapter identifies method inputs that meet our standard of practicality. Bedrooms, unit type and block group are practical housing unit descriptors. The method's output is the expected vehicle availability for a household in a given block group, of a given unit type, including a given number of bedrooms. The next chapter completes our method development by proposing a method to link our inputs to the desired output, and validating the method using independent household survey data.

Chapter 4. A validated method for estimating household vehicle availability

Preceding chapters have laid the groundwork on which to develop a practical method for estimating household vehicle availability. Chapter 1 set the regulatory context and illustrated the need for an improved method for setting residential parking standards. Chapter 2 reviewed the literature on the estimation of household vehicle availability to discern the current thinking on the most important predictors of and covariates with household vehicle availability. Chapter 3 demonstrated how these important predictors can be proxied with variables that are practical for parking regulations: unit type, bedrooms and location.

This chapter takes the next and final step in this research: to present and validate a novel and practical method for estimating household vehicle availability. We consider all three practicality criteria here. First, the method should be inductive: relying heavily on observation. Second, the method should be adequate and valuable: processing data in a scientifically sound way to create accurate estimates with low uncertainties. Third, the method should be married to the decision process: reflecting the group decision-making context in which the resulting new standards will be used. The following sections describe the method and its relationship with findings presented earlier in this text, present data and methods used to evaluate this new method, and discuss the results.

VULO: Vehicles from Unit choice with a Location-based Offset

This section presents a method for estimating household vehicle availability from publicly available data: the culmination of the preceding chapters. In the first step, PUMS data are used to develop a preliminary estimate of vehicle availability by bedrooms, unit type and PUMA. Second, the results of the first step are used to develop an estimate of block groups' average vehicle availability. In the final step, the difference between the block group vehicle availability averages reported by the Census and the estimates are used as location-based offsets to refine the estimates from step 1. This method is called the VULO method, for Vehicles from Unit choice with a Location-based Offset. It is described in detail below. Appendix D contains a worked example.

Step 1: Regress vehicles on unit type and bedrooms at the PUMA

Method The first step is to make the best estimate of household vehicle availability possible with a straightforward application of publicly available data. In this step, household vehicle availability is regressed on unit type and number of bedrooms on a PUMA by PUMA basis. That is, vehicles are estimated as

$$\hat{v_{u,BR,PUMA}} = a_{u,PUMA} + b_{PUMA} BR \quad (4.1)$$

where subscripts indicate the dimensions of the variables. For example, $a_{u,PUMA}$ is a matrix that may take on unique values for all combinations of unit type and PUMA.

This analysis is conducted at the PUMA because it is the smallest unit of analysis at which vehicles can be tabulated by unit type and bedrooms using publicly available data, and smaller is better. Table 3.5 shows that the effect on vehicle availability of increasing the number of bedrooms depends on the population density of the PUMA of residence. Table 3.7 demonstrates the same fact using a regression analysis. There is ample evidence that the relationship among unit type, bedrooms and vehicles available is moderated by location. The work in Table 3.16 indicates that the influence of location on vehicle availability is better captured at the block group than the tract level. Analysis of the PUMS indicates that the same is true at larger geographies: tabulating vehicle availability by unit type and bedrooms at the PUMA rather than at the state captures more of the variance in the data for the New Jersey case: 27.8% versus 23.4%[22]. The best we can do as a starting point is to use data tabulated at the PUMA.

Table 3.7 indicates that the relationship between vehicles and bedrooms is moderated by unit type. However, the formulation of VULO's Step 1 does not accommodate that fact. It assumes that the sensitivity of vehicles available to bedrooms is independent of unit type, within a PUMA. This simplification is necessary to conduct Step 2, given the limitations of the data available. In particular, the distribution of bedrooms by unit type is not publicly available at any unit smaller than the PUMA. This problem is clarified in the discussion of Step 2.

Data required Step 1 of the VULO method requires only the PUMS for the area of the regulator's interest. For example, developing statewide standards would require PUMS data from the entire state. The PUMS records required are vehicles available, bedrooms, and units in structure.

Step 2: Estimate average vehicles per household at the block group

Method The middle step in the VULO method is to estimate average vehicles per household for the block groups in the given PUMA. As described below, this allows us to estimate the positive or negative influence that the block group's location within the PUMA has on its households' vehicle ownership, on average. In this step, we simply populate the equation presented in Step 1 with block group-average bedrooms per

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[22]These r^2 values are computed by computing average vehicle availability by unit type (eight levels) and bedrooms (six levels), for all structured (immobile) housing units in the New Jersey PUMS.

household and the fraction of all households that fall into each unit type. This produces an estimate of the average vehicles per household in the block group. It is expressed as an equation as follows:

$$\hat{v_{BG}} = a_{u,PUMA}\, ufrac_{u,BG} + b_{PUMA}\, BR_{BG} \quad (4.2)$$

where

- $\hat{v_{BG}}$ is the estimated average vehicle availability for all households in the given block group;
- $ufrac_{u,BG}$ is the fraction of all households in block group *BG* that fall into unit type *u*;
- BR_{BG} is the average number of bedrooms per household in block group *BG*; and
- the regression coefficients *a* and *b* have the same meaning as in Equation 4.1.

Equation 4.2 is a proper extension of Equation 4.1 to compute average block group vehicle availability. First, Equation 4.1 linear in parameters and variables, and can be averaged over any area within a PUMA. Second, based on the discussion in Chapter 3, the block group is our optimal areal unit. The result of Equation 4.2, therefore, is a consistent estimate of the average household vehicle availability at the geographic unit level—our specification of location—at which we wish to compute estimates of household vehicle availability.

However, this estimate of average vehicle availability is biased. It is built on Equation 4.1, which is derived from an analysis of households across the PUMA. To extent that the unit type-bedrooms-vehicles relationships that characterize the entire

PUMA sample differ from the unit type-bedrooms-vehicles relationships that characterize the block group, the result of Equation 4.2 will be biased. The magnitude of the bias depends entirely on the systematic differences between the PUMA sample and the block group sample. That is, Equation 4.2 produces an estimate of block group average vehicle availability that ignores the difference between the block group's local vehicle-related characteristics and the PUMA's vehicle-related characteristics. This bias, the block group-averaged influence of the differences between the block group characteristics and the PUMA characteristics, is termed the “local offset,” and is the essence of the VULO method.

Data required The data required for Equation 4.2 are the block-group average bedrooms per household and the fraction of block group households that fall into each category of unit type. These data are available from the Decennial Census Summary File 3 (SF3), which includes tabulations of all long-form responses, weighted to approximate the total household population of the area. The fact that the SF3 does not tabulate bedrooms per household by unit type is what prevents Equation 4.1 from including the fact that the relationship between bedrooms and vehicles is moderated by unit type.

Step 3: Compute and apply the local offset

The final step in the VULO method is to quantify the bias discussed above and use it to capture the effect of location on vehicle availability. The difference between the measured block group average vehicle availability and the average vehicle availability computed via Equation 4.2 is the local offset. Adding this local offset to Equation 4.1 produces an estimate of household vehicle availability that goes beyond it by reflecting the differences between the block group and its home PUMA.

$$LO_{BG} = v_{BG} - \hat{v_{BG}} \quad (4.3)$$

where v_{BG} is reported by the Census Bureau and $\hat{v_{BG}}$ is computed according to Equation 4.2. The final equation is

$$v_{u,\hat{BR},BG} = a_{u,PUMA} + b_{PUMA} BR + (v_{BG} - \hat{v_{BG}}) \quad (4.4).$$

The rationale for the implementation of the local offset in Equation 4.4 has been discussed above; a further benefit of this implementation is that the block group average of its household vehicle availability estimates is equal to the measured block group average vehicle availability.

The VULO method is designed to be easy to apply while maintaining a strong link to the theory of vehicle ownership: it is practical while being context-sensitive. As to practicality: meeting the first criterion, it is inductive. It relies heavily on measured household vehicle availability, but uses known relationships among predictors of vehicle availability to extend and refine estimates from the data. It is adequate, in that it uses a scientifically sound description of the housing unit and plausible data processing methods to estimate a result. (The second half of criterion #2, regarding value/accuracy, is left to later in this chapter.) It is married to the decision process, relying on housing unit descriptors commonly used by parties to parking regulation negotiations. It satisfies our working definition of practicality.

The VULO method's design anticipates communicative challenges as well. Andrews (2002) calls for practical analysis to be shared widely. (See Table 3.1.) The VULO method heeds that call in two ways. It is simple to implement, involving few steps and publicly available data[23]. It is simple to explain, which helps with adoptability and also lends face validity.

The balance of this chapter tests the VULO method's value, or, in shorthand, accuracy.

Data

This chapter contains a handful of distinct analyses that draw on the same three sets of data. This section describes those data sources, all of which come from the 2000 Decennial Census for New Jersey: a custom tabulation of Census data, the PUMS, and Summary File 3. New Jersey is the most densely populated state in the country, and exhibits a wide range of built environments. It is bounded by two major employment centers—New York City and Philadelphia—and also hosts significant job concentrations within its borders, in cities such as Jersey City and in sprawling pharmaceutical campuses in central New Jersey. It is served by an extensive public transit system including trains and buses, as well as a massive road network. New Jersey makes an interesting case because of its activity intensity and land-use diversity.

[23]In 2010 and beyond, the Decennial Census will not include long-form questionnaires, results from which form the basis of the VULO method. However, this will not affect future implementation of the VULO method. Instead of the long form, the Census Bureau has implemented the American Community Survey (ACS). The ACS is administered to 1% of households annually, and contains many of the items formerly contained in the long-form Decennial Census survey, including the items used in the VULO method. Microdata are released annually, one year after surveys are completed, and are linked to the same 5% PUMAs used in this research. ACS PUMS data from 2005 are currently publicly available; for New Jersey, the 2005 ACS PUMS data include roughly 1/10th the number of households included in the 2000 Decennial Census PUMS. Five-year averages of data aggregated at the levels of Census tract and block group will be released annually starting in 2010. That is, the ACS provides the data necessary for the VULO method roughly as well as the Decennial Census PUMS does. The only practical difference is that the ACS is distributed over time, with small annual administrations, whereas the Decennial Census offers a clear snapshot once every ten years.

Special Census Tabulation

The key data that make this analysis possible are the special Census tabulations of number of households by vehicles available, bedrooms, unit type, and block group. This is a set of data custom ordered from the Census Bureau. It includes the 3,900 block groups in New Jersey that had at least 50 long-form respondents in 2000; this is 61% of New Jersey's block groups containing at least one household. Note that the 50-respondent threshold equates roughly to a minimum block group population of 300 households, given the 1 in 6 sampling goal for the long-form questionnaire.

In addition to the block group code, the special tabulation contains three essential data fields: vehicles available, unit type, and bedrooms. Vehicles available and bedrooms both have five levels: 0, 1, 2, 3, and 4 or more. Unit type comes in four levels: single-family detached, single-family attached, in a building with a total of two to four units, or in a building housing five or more units.

PUMS

The second data set involved is the 2000 Decennial Census's 5% Public Use Microdata Sample (PUMS). In this sample, the detailed responses of one in every twenty households are provided to the public, along with the household location in terms of its resident Public Use Microdata Area (PUMA). PUMAs have a population of at least 100,000 people.

In the PUMS there are four data fields useful for our purposes here. Household vehicles available, which includes those owned, leased, provided by an employer, or otherwise regularly available to household members, are reported in seven levels: zero through six or more. Bedrooms in the household are reported at six levels: zero through five or more. Unit type ("units in structure") is reported in two mobile categories and eight levels of fixed-structure housing: single-family detached, single-family attached, two units in structure, three to four units, five to nine units, 10 to 19 units, 20 to 49 units, and 50 or more units. To facilitate comparisons with the purchased special tabulation, these eight levels were collapsed to the four in the tabulation.

Census Summary File 3

An additional publicly available data set is needed here: the standard tabulations of long-form responses contained in the 2000 Census Summary File 3 (SF3). This product differs from the PUMS in three respects relevant to this research. First, it is drawn from all long-form responses representing about 17% of the population, rather than merely 5%. Second, it presents results at geographies as small as the block group, which has a target population of 1,500, rather than only the PUMA, which has a minimum population of 100,000. Third, not all long-form responses are tabulated against each other, as is possible with the microdata in the PUMS.

SF3 contains three tables that are used here. First, aggregate vehicles available in the block group, when combined with total occupied households in the block group, provides a reported average vehicles per household. Second, households by unit type allows the calculation of the fraction of all block group households that fall into each unit type category. The Census reports households in each of eight categories of fixed-structure housing; for this research, these eight categories are collapsed into the same four in the special tabulations. Third, households by bedrooms allows calculation of the block group average number of bedrooms per household.

Method

In this section we consider five benchmark methods for estimating household vehicle availability, against which we can compare the VULO method. Two of the benchmarks represent the upper limit on data fit possible with any method—the block group and tract average household vehicle availability, controlling for bedrooms and unit type. As the VULO method considers only location, unit type and bedrooms, no other variable is available to explain any within-cell variation, and averaging all households within a given unit type/bedrooms/location cell gives the best fit to the data in a least squares sense. A third benchmark represents state of the practice in New Jersey: statewide average vehicle availability by unit type/bedroom combination. The fourth benchmark is presumably inferior to the VULO method implemented at the block group level—the VULO method implemented at the tract. The fifth method, perhaps the most viable alternative to the VULO method, requires significant explanation.

The PUMA-regression method, uses bedroom, unit type, and vehicles available data at the smallest geographic unit at which it is publicly available—the PUMA. The simplest way to use these data would be to create a look-up table for each PUMA, indicating for each combination of unit type and bedrooms what is the average household vehicle availability. However, not all PUMAs have households in all unit type by bedrooms combinations of interest. Therefore, and to minimize the influence of spuriously high or low cell vehicle averages due to low but nonzero cell counts, the PUMA level data are represented by a regression equation:

$$\hat{v} = a_{u,PUMA} + b_{u,BR,PUMA} BR \quad (4.5).$$

This equation handles bedrooms differently than does the equation used in the VULO method (Equation 4.4). In that method, the sensitivity of vehicle ownership to number of household bedrooms is independent of unit type. This is necessitated by the limitations of the publicly available Census data used to estimate the block group-average vehicle availability: the Census Bureau does not report the distribution of bedrooms by unit type. The PUMS does allow that computation for a PUMA, however, which enables the regression equation in the PUMA-regression method, Equation 4.5, to include the influence of unit type on the sensitivity of vehicle availability to bedrooms. In other words, Equation 4.5 represents separate regression equations for each unit type.

The VULO method is compared against the PUMA-regression method using all 3,900 block groups in the special tabulations. However, the VULO method is compared against block group and tract averages, and against the tract-level version of the VULO method, using only those block groups that compose complete tracts. Of the 3,900 block groups in the purchased sample, 1719 block groups compose 729 complete tracts. These 729 tracts represent 37.6% of the 1938 tracts in New Jersey containing households, and 36.0% of all the housing units in New Jersey.

Aggregate validation

The initial step in validating the VULO method is to consider its fit to the data in an aggregate sense. In this section, benchmarks for data fit are proposed and evaluated, the VULO method is implemented, and their results are compared. The aggregate validation results suggest that the VULO method outperforms the two alternative methods.

Table 4.1. Comparing methods for estimating household vehicle availability

Method	***r^2***
Block group averages by unit type and BR	0.421[2]
Tract averages by unit type and BR	0.386[2]
State averages by unit type and BR	0.270[1]
VULO at the tract	0.337[2]
PUMA-level regressions	0.300[1]
VULO (at the block group)	**0.332[1] / 0.345[2]**

[1]Computed using all 3,900 block groups present in the special tabulations.
[2]Computed using a subset: 1,719 block groups that fully compose 729 tracts.

Table 4.1 reports the VULO method results alongside the benchmarks. The first row indicates the fit between the survey data and the data's averages by block group and unit type/bedroom combination. Using block group averages captures 42.1% of the variation in household vehicle availability. Using tract averages instead captures 38.6% of that variation. (As discussed above, the difference between the two approaches is statistically significant. See Table 3.16.) Averaging household vehicles over the entire sample produces the result in the third row, capturing 27.0% of the variance. Implementing the VULO method at the tract captures 30.0% of the variation in the data, as does the PUMA-regression method. (Note, though, that they were exercised on different data sets.) The VULO method captures less variation than the straightforward averages of the data, which are upper limits on the method's data fit. It performs better than the two alternative methods: VULO at the tract (although this difference is not significant—see below) and the PUMA-level regressions method, which allows for the influence of unit type on the sensitivity of vehicle availability to bedrooms.

By comparing Table 4.1 to the regression results in Chapter 3, we can roughly assess the trade-off between context-sensitivity and practicality. First, consider Table 3.12. It presents a model of household vehicle availability in north and central New Jersey where location is proxied as the density of the residence PUMA, and household income and work status is included. It captures 44% of the variance in the data. Excluding household sociodemographic variables from that model leads to a model that captures 25% of the variance, as shown in Table 3.7. The VULO method falls between these points. Relative to the full regression in Table 3.12, the VULO method is more geographically precise, but includes no demographic information. The result is that the benefit that the VULO method offers due to its refined geographic controls, relative to a baseline method that weakly controls location (PUMA density only), is roughly[24] half as great as the benefit offered by introducing demographic data.

Table 4.2 shows that the VULO method does not offer a statistically significantly better fit to the data when exercised at the block group level rather than the tract. The sample used here contains 1,719 block groups that compose 729 complete tracts. The number of coefficients in each model is the number of unit type x bedrooms x areal unit cells that contain households. Each of these cells has a computed average household vehicle availability, and these averages constitute the models. If every cell in the sample contained households, the block group-level model would contain 1,719 x 4 (levels of unit type) x 5 (levels of bedrooms) = 34,380 averages. Because some cells contain no households, K_{BG} in Table 4.2 (15,611) is less than this number (34,380). Properly

[24]This comparison is particularly rough because the studies in Chapter 3 use a different sample of households than do those in Chapter 4.

estimating the degrees of freedom in this way leads to a computed F of 0.30. Given the degrees of freedom listed in Table 4.2, this is not significant at p=0.1.

Table 4.2. F test comparing method executed at tract or block group

Number of block groups	1,719	Number of tracts	729
K_{BG}	15,611	K_{TR}	8,992
SSE_{BG}	657,084	SSE_{TR}	665,059
		Number of households	1,077,453
		T	179,576
		DOF_numerator = $K_{BG} – K_{TR}$	6,619
		DOF_denominator = $T – K_{BG}$	163,965
		$F = [(SSE_{TR} – SSE_{BG})/(K_{BG} – K_{TR})]/[(SSE_{BG}/(T – K_{BG})]$	0.30

This analysis demonstrates that the method developed in this research does not capture variation in the available data better when applied at the block group level than at the tract level. That is, reducing the geographic area of analysis and the sample size from the tract to the block group does not statistically significantly increase the proportion of variation in household vehicles that is associated with bedrooms and unit type. This contrasts with the analysis in Chapter 3, which demonstrated that the measured variation in the available data is better captured at the block group level. Whereas the analysis in Chapter 3 shows that household vehicle availability, controlling bedrooms and unit type, varies significantly among block groups, Table 4.2 shows that the VULO method does not capture this variation.

This section demonstrates three important points about the VULO method. First, it is not better implemented at the block group than at the tract. Second, it fits the data less well than the relevant optimal benchmark approaches: averaging vehicle availability by block group and tract. Third and most importantly, it fits the data better than viable alternatives such as the current New Jersey practice of using statewide vehicle availability averages or the more sophisticated PUMA-regressions approach.

Disaggregate validation

It is useful to disaggregate the VULO method's predictions and errors. From a practical perspective, users need to know as much as possible about the conditions under which the VULO method performs well and badly. It is also valuable to know whether alternative methods outperform the VULO method in some situations.

Results: VULO mean and standard error

Figure 4.1 shows how the VULO method error varies with unit type, bedrooms and population density. Each image in the figure represents a different sample of block groups taken from the 3,900-block group sample in the special Census tabulation. The 3,900 block groups were broken into population density deciles. The first image represents the second decile, comprising 390 block groups with an average block group population density of 1,028 residents per square mile. This decile was chosen for display because its mean density falls near the Census bureau's criterion density for an urbanized area. The other deciles, the sixth and eighth from the sample, were chosen for the proximity of their mean densities to 5,000 and 10,000 residents per square mile.

Each image shares three dimensions. The horizontal axis indicates the number of bedrooms in the unit, from zero to four. The vertical axis indicates the unit type: single-family detached unit (SFD), single-family attached unit (SFA), unit in a two- to four-unit building, and unit in a building with five or more units. The values indicated by the contours are the mean method error at the given combination of unit type and bedrooms, averaged across all households in the 390 block groups in the decile.

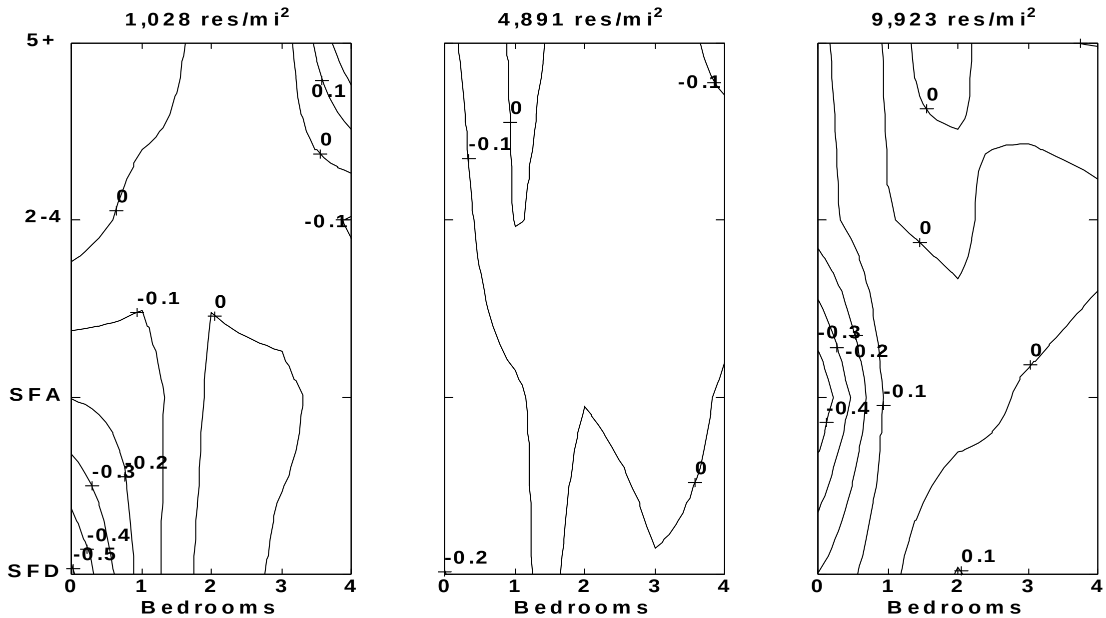

Figure 4.1. Mean error (household vehicles) from VULO method

Figure 4.1 indicates that the VULO method is biased as follows. In the low density sample, the VULO method substantially underpredicts household vehicles for zero-bedroom SFDs and overpredicts vehicles for four or more-bedroom units in five or more-unit buildings. The VULO method also substantially underpredicts household vehicles for zero-bedroom SFAs in the high density sample. One likely contributor to this pattern is the assumption that vehicle availability is linearly related to bedrooms over a range from zero to four or more. The substantial error gradients at the extreme values of bedrooms suggests that this assumption is less tenable there than in the middle of the bedroom range. Other explanations for the error patterns are explored below.

Figure 4.2 presents the standard error from the VULO method, using the same format as Figure 4.1. This figure is of particular practical importance because vehicle estimates from the VULO method, when presented with 95% confidence intervals, are given as the estimate +/- twice the standard error. Figure 4.2 reflects the findings in Figure 4.1 to some extent, as the cases with the largest mean errors are also among the cases with the largest standard errors: consider zero-bedroom SFDs at low density and zero-bedroom SFAs at high density. High standard error also occurs at four or more bedrooms in multifamily units in the densest sample. These are likely driven by unobserved differences in household income and number of workers and nonworking adults—units with more bedrooms are prone to admit more variability in these characteristics than units with, say, one or two bedrooms.

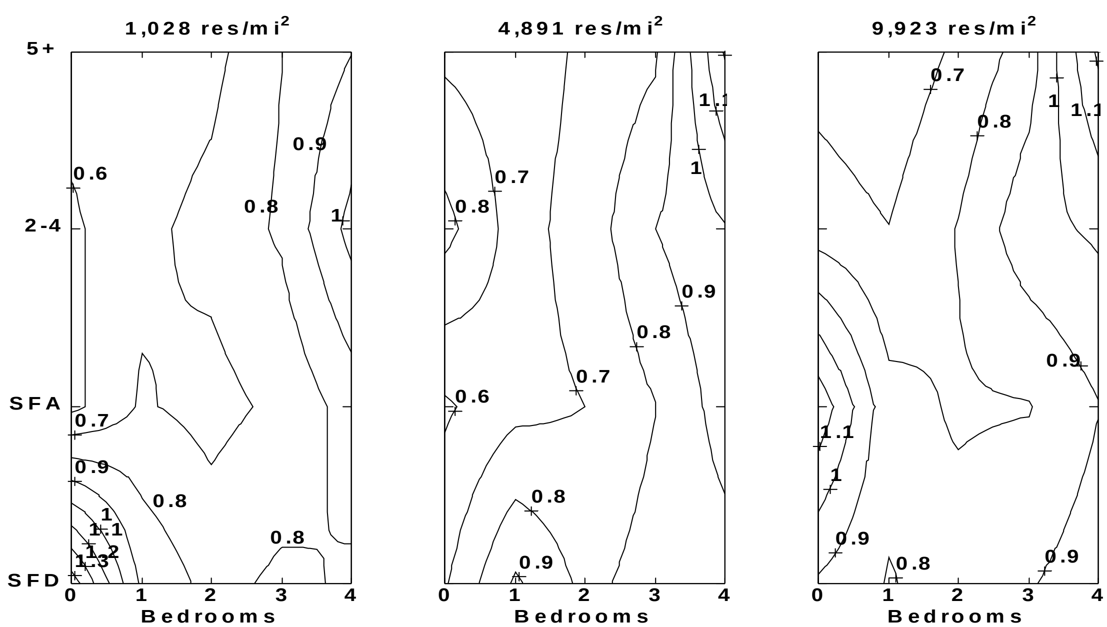

Figure 4.2. Standard error (in household vehicles) from the VULO method

Discussion: Understanding error

It is useful at this point to present a rough theory of the VULO method. Doing so should allow a more thoughtful discussion of its performance in different realms of unit type, bedrooms and location. We can develop this theory using tools previously presented: the description of the VULO method, at the start of this chapter, combined with omitted variable bias analysis discussed in Chapter 3.

We start with an expression for the number of vehicles available to household *i* in block group *j*.

$$v_{ij} = \alpha_1 u_{ij} + \beta_1 BR_{ij} + \gamma D_{ij} + \lambda L_j + \epsilon_{ij} \quad (4.6)$$

In this expression, u_{ij} is the unit type[25]. BR_{ij} is the number of bedrooms in the household. D_{ij} is a set of demographic variables such as household income. L_j is a set of location-related variables such as population density. For consistency with the VULO method, this and subsequent equations each take a single PUMA as their domain.

In step 1 of the VULO method, we approximate household vehicle availability by omitting demographic and locational variables.

$$\hat{v}_{ij} = \alpha_2 u_{ij} + \beta_2 BR_{ij} \quad (4.7)$$

Note that Equation 4.7 is a restatement of Equation 4.2.

The conclusion of the VULO method is to adjust Equation 4.7 by the location-based offset appropriate to block group *j*. That offset is the difference, averaged over all households in block group *j*, between v_{ij} given by Equation 4.6 (and actually measured and reported by the Census Bureau) and $\hat{v}_{ij}$ from Equation 4.7. Accordingly,

[25]It is easiest to think of it as a scalar multiplied by a scalar α_1, although the equations hold equally well if both are vectors, as is the case with the VULO method.

$$v_{ijVULO}=\alpha_2 u_{ij}+\beta_2 BR_{ij}+[(\alpha_1-\alpha_2)\bar{u}_j+(\beta_1-\beta_2)\bar{BR}_j+\gamma\bar{D}_j+\lambda L_j+\bar{\epsilon}_j] \quad (4.8).$$

The error from using the VULO method is the difference between v_{ijVULO} and v_{ij} from Equation 4.6. Combining and rearranging, we have

$$E_{ij}=(u_{ij}-\bar{u}_{ij})(\alpha_2-\alpha_1)+(BR_{ij}-\bar{BR}_j)(\beta_2-\beta_1)+(D_{ij}-\bar{D}_j)(-\gamma)+\bar{\epsilon}_j-\epsilon_{ij} \quad (4.9).$$

$(\alpha_2-\alpha_1)$ and $(\beta_2-\beta_1)$ are omitted variable biases attending the simplification of Equation 4.6 that results in Equation 4.7. This motivates the regression of the omitted variables on the included variables, following the traditional approach in omitted variable bias analysis (Imbens, 2005).

$$D_{ij}=d_u u_{ij}+d_B BR_{ij}+\epsilon_{Dij} \quad (4.10)$$

$$L_{ij}=l_u u_{ij}+l_B BR_{ij}+\epsilon_{Lij} \quad (4.11)$$

Combining Equations 4.10-11 and Equation 4.6, we have:

$$\hat{v}_{ij}=(\alpha_1+\gamma d_u+\lambda l_u)u_{ij}+(\beta_1+\gamma d_B+\lambda l_B)BR_{ij} \quad (4.12).$$

Combining this with Equation 4.7 gives:

$$\alpha_2-\alpha_1=\gamma d_u+\lambda l_u \quad (4.13),$$

$$\beta_2 - \beta_1 = \gamma d_B + \lambda l_B \quad (4.14).$$

Finally, combining Equations 4.9 and 4.13-14 gives

$$E_{ij} = (u_{ij} - \bar{u}_j)(\gamma d_u + \lambda l_u) + (BR_{ij} - \bar{BR}_j)(\gamma d_B + \lambda l_B) + (D_{ij} - \bar{D}_j)(-\gamma) + \bar{\epsilon}_j - \epsilon_{ij} \quad (4.15).$$

Before exploring the implications of this expression, let us confirm its reasonableness. The first term is an estimate of the error introduced by the fact that the given household's unit type is not the average unit type that is used in the computation of the location-based offset. It is the product of the difference between the household unit type and the block group average unit type and the indirect sensitivity of vehicles to unit type. γd_u is the sensitivity of vehicles to demographics multiplied by the sensitivity of demographics to unit type; it could be restated as $\frac{\partial v}{\partial D}\frac{\partial D}{\partial u}$. Likewise, λl_u is equal to $\frac{\partial v}{\partial L}\frac{\partial L}{\partial u}$. An equivalent discussion applies to the bedroom term. The third term is the difference between household demographics and block group average demographics, multiplied by the sensitivity of household vehicles to those demographics.

What does Equation 4.15 tell us? First, the VULO method's error is not directly related to the environmental variables L. This is not to say that the VULO method's error is independent of location; Figures 4.1 and 4.2 show that it does vary with location. Equation 4.15 merely indicates that these effects are mediated by demographic and other variables (in the error term).

Second, Equation 4.15 shows that the block group average VULO method error is zero. Each of the terms, including the error term, falls to zero when the equation is averaged over block group *j*.

Third, the magnitude of error from the VULO method tends to increase as the household in question differs more from the block group average household. This is true in both residential unit choice and demographic terms.

Further observations require us to say something about the values of the parameters in the equation. Thanks to work in Chapter 3, that is possible if we assume that density is the only locational variable and household income is the only demographic variable in the equations. For the purposes of exposition, let us further assume that unit type is a scalar variable takes the value of 1 for an SFD, 2 for an SFA, and so on.

For one, we can argue that the indirect sensitivity of vehicles to unit type, $(\gamma d_u + \lambda l_u)$ is likely negative. γ, the sensitivity of vehicle availability to household income, controlling unit type, bedrooms and location, is positive. d_u, the sensitivity of household income to unit type, is (generally) negative, and their product is negative. λ is the sensitivity of vehicles to density controlling for unit type, bedrooms and income, and is negative. l_u is the sensitivity of block group density to average unit type, and is positive. Their product is also negative, and the sum of these two products, $(\gamma d_u + \lambda l_u)$, is negative.

On the other hand, the indirect sensitivity of vehicles to bedrooms, $(\gamma d_B + \lambda l_B)$, is likely positive. The preceding paragraph argues that γ is positive and λ is negative. d_B is the sensitivity of household income to bedrooms, and is positive, whereas l_B, the sensitivity of density to bedrooms, is likely negative. This gives us the product of two positive numbers as the first term and the product of two negative numbers as the second term, the sum of which is positive.

The fourth and final observation on Equation 4.15, then, is that the VULO method error depends in opposite ways on bedrooms and unit type. We should expect to see negative errors with the greatest magnitude for households with many fewer bedrooms than the block group average and in a unit that is more attached than average. Conversely, we should expect positive errors with the greatest magnitude for households with many more bedrooms than the average, living in an SFD in a block group dominated by multifamily units.

Figure 4.1 does not show the predicted pattern. This indicates that the systematic error due to the indirect impacts of unit type and bedrooms are overwhelmed by the errors introduced by unobserved variables such as household income[26]. As mentioned above, the shape of the error fields in Figure 4.1 suggests that the linear influence of bedrooms coupled with the wide range of bedroom levels may be problematic. Figure 4.3 shows that zero-bedroom units are rare in all three samples[27], indicating that perhaps the zero-bedroom category should be removed in future analysis.

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[26]This is consistent with the analysis in Chapter 3. Compare Tables 3.7 and 3.12 to see that demographics are very important in explaining vehicle availability.
[27]Note that with twenty cells for each sample, the average cell population is 5%.

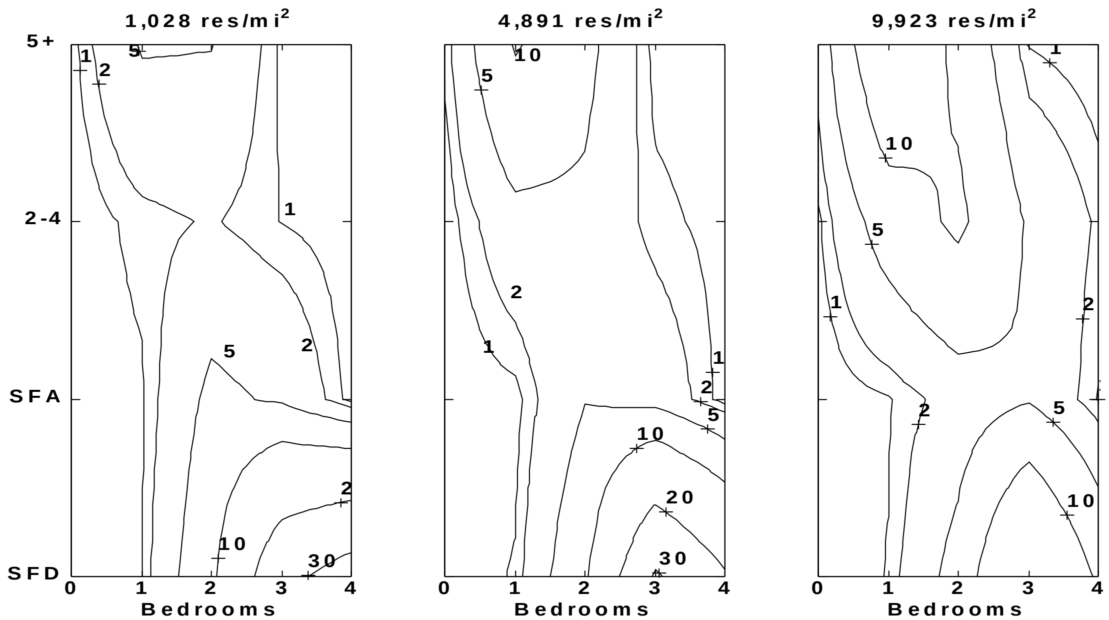

Figure 4.3. Percentage of sample households in each unit type/bedroom cell

Discussion: Comparing VULO to alternative methods

Under what conditions does the VULO method perform best and worst? This section answers that question by comparing it against two benchmarks.

Statewide averages The first is based on the approach used in the State of New Jersey's Residential Site Improvement Standards (RSIS). The RSIS establishes a minimum off-street parking spaces per unit of housing on the basis of bedrooms and unit type. The standard is applied to all newly constructed housing in the state, with city- and project-specific exceptions. (See Table 3.2 for details.) We approximate an updated version of that approach by computing a table of statewide average household vehicle availability, using the data from all households in the 3,900 block-group special tabulation, and crossing the household characteristic levels available in the special tabulation of Census 2000 data: zero to four bedrooms by unit type—single-family detached, single-family attached, in a structure containing two to four units, or in a structure containing five or more units[28]. (This is the same method used to produce the third row in Table 4.1.)

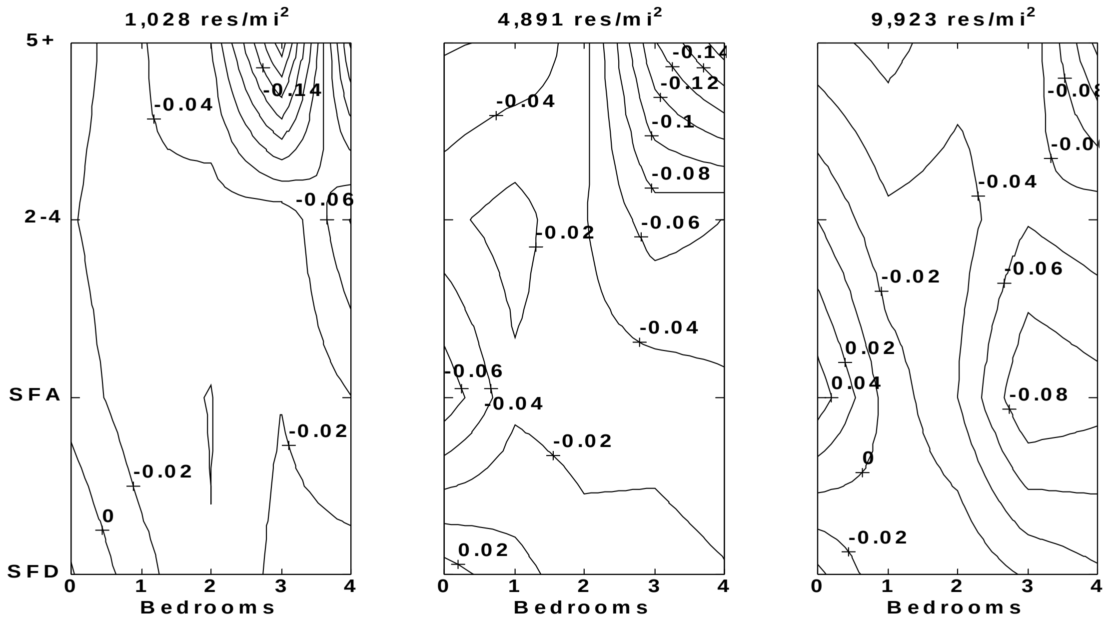

Figure 4.4. Change in std. error: VULO - statewide averages

Figure 4.4 illustrates the precision benefit provided by the VULO method relative to the NJ RSIS approach, at three population density levels in the sample. Negative numbers indicate where the VULO method produces a lower standard error than the statewide average. Each image in the figure is based on the difference between the standard error from the RSIS approach and the standard error from the VULO method. To compute the standard error for either method, household-level error was computed by subtracting the reported vehicle availability from the amount estimated by the method at hand. These errors were then partitioned by unit type, bedrooms, and population density of the block group. Block groups were aggregated into density deciles. Errors in a given

[28]Note that RSIS standards were computed using statewide averages of vehicle availability considering only recently constructed housing. In contrast, the statewide average approach here includes units of all ages.

combination of bedroom, unit type, and density decile were squared, summed, divided by one less than the number of households in the cell, and then raised to the ½ power.

Figure 4.4 shows that the VULO method is more precise than the statewide method across block group density, unit type and bedrooms. The only exceptions are at low and medium density, for zero-bedroom single-family detached units (SFDs), and at high density, for zero-bedroom SFAs. The VULO method's precision advantage over the statewide lookup is generally higher for multifamily units and for units with more bedrooms. As denser areas tend to host more multifamily housing (see Appendix C), this suggests that VULO's advantage is greater in urban areas.

PUMA-regressions The second alternative method for estimating household vehicle availability is called the PUMA-regressions method. It is described above, and reviewed here. In the PUMA-regresssions method, household vehicle availability is estimated as a unit type-specific constant plus the product of a unit type-specific coefficient and the number of bedrooms. The PUMA-regressions method has the advantage over the VULO method of allowing the sensitivity of vehicles to bedrooms to be unit-type dependent. It has the relative disadvantage of accounting for the effects of location at the PUMA (population >100,000), however, rather than at the much smaller block group (population ~1,500).

These competing differences raise the question of how the PUMA-regressions method compares with the VULO method. Table 4.1 indicates that overall, the VULO method fits the special tabulation Census data better than the PUMA-regressions method. Here we consider how the two methods compare in a disaggregated way.

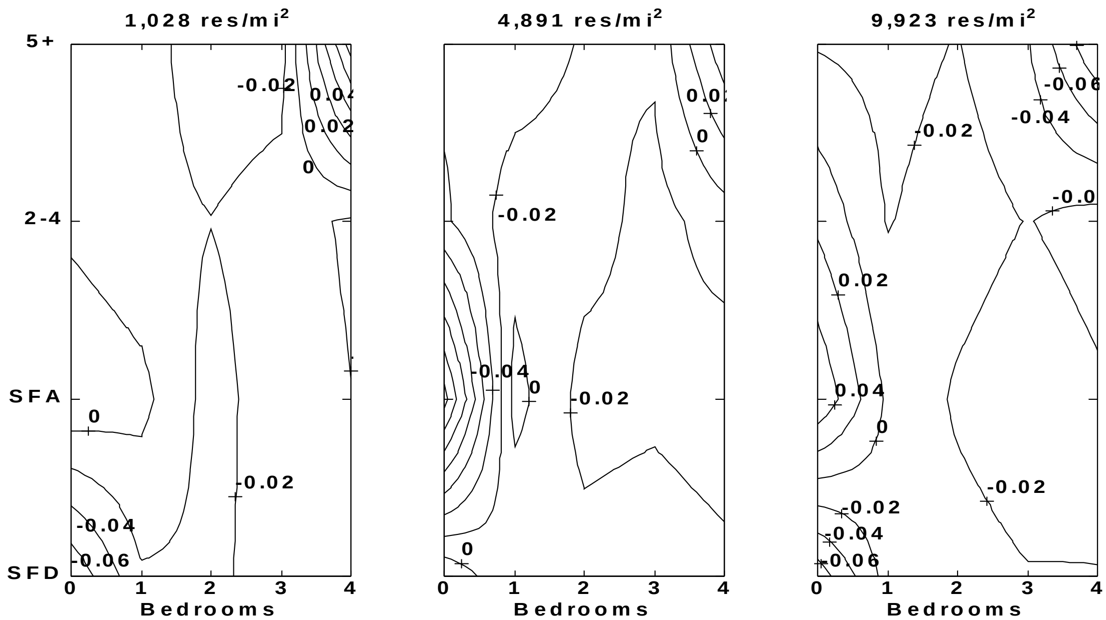

Figure 4.5. Change in std. error: VULO - PUMA-regressions

Figure 4.5 shows that almost universally, the VULO method is more precise than the PUMA-regression method. Negative numbers indicate that the VULO method produces estimates with lower standard error than the PUMA-regressions method. The major exceptions are in three cases:

1. in the low density sample, four or more-bedroom units in five-plus-unit buildings
2. in the medium density sample, the same bedroom/unit type combination, and
3. in the high density sample, zero-bedroom units in SFAs.

For these cases we can conclude that the VULO method's benefit of including local effects at the block group is outweighed by its limitation of assuming that a single-bedroom increment is associated with the same vehicle increment, regardless of unit type. This latter assumption appears particularly untenable for the three cases in part because of their rarity: observe in Figure 4.3 how far the 1% contour is from the three cases.

Conclusions

This chapter represents the culmination of this research. It presents and validates the VULO method, a practical method for estimating household vehicle availability. This method involves three steps. First, household vehicle availability is estimated by linearly regressing vehicles on bedrooms and unit type on a PUMA by PUMA basis. Second, block group-average household vehicle availabilities are estimated by averaging the equations from step 1. Third, the equation from step 1 is corrected by the difference between actual and estimated block group average vehicle availability. The result is a data-driven method that uses household unit and vehicle data at the smallest geography at which household data are publicly available to infer the influence on vehicle availability of location within that area.

The method meets our three criteria for practicality.

First, it is inductive: The VULO method is based primarily on data, relying on theory only tangentially.

Second, it is "adequate" and "valuable." Here we use scientifically sound as shorthand for "adequate," and the VULO method is scientifically sound. It uses housing unit descriptors that exhibit consistent and predictable relationships with vehicle availability. Consistent with the literature review in Chapter 2, it decomposes the determinants of vehicle ownership into location-related variables and demographic variables (including attitudinal variables). The VULO method first accounts for the somewhat location-specific effect of demographics, proxied by residential unit choice. Then it corrects the estimate based on a refined measure of location. Also, its data processing procedures are defensible.

As to value, we address that criterion by considering standard error in method projections. In an aggregate sense, the VULO method outperforms both the current practice—statewide averages by unit type and bedrooms—and also a refinement of that practice (PUMA-regressions). The disaggregated validation results show that the VULO method consistently outperforms both the current practice and its refinement. In the rare unit type/bedrooms/density combinations where the VULO method does not outperform the alternatives, the problem appears strongly linked to the VULO method's assumption that throughout the PUMA, the sensitivity of vehicles to bedrooms is constant.

The VULO method's relatively low error is the result of a series of method design decisions aimed to manage aggregate error throughout the process. Considering input variables, number of bedrooms is chosen over unit floor area because survey respondents, whose responses would create tables for regulation, are presumed to be unable to answer the question reliably.

Similarly, part one of the VULO method was redesigned to manage uncertainty. An initial version of the method tabulated average vehicle availability by bedrooms and unit type for every PUMA. However, because some cells in these tables contained a very small number of households, the standard error of the means were substantial. In fact, some tables showed counterintuitive trends, and numerous cells were empty. Using regression instead averages away idiosyncratic behavior and offers a consistent method for filling empty cells. On the other hand, as discussed above, the assumption that the sensitivity of vehicles to bedrooms is independent of unit type, as required by the data available for the regression method, surely introduces some error. The validations above show that the costs of the design decisions made here do not outweigh the benefits.

Third, it is married to the decision process. It uses housing unit descriptors that are widely used in current parking regulation practice. It is conceptually simple: estimate household vehicle availability using PUMS data and then correct that estimate according to the difference between block group average vehicle availability and the PUMA-level trends. Also, it can produce readily usable tables—see Appendix D.

Looking ahead to broad implementation, we should also consider the utility of the VULO method in places other than New Jersey, the source of all data used in this research. The validation results and analysis of the VULO method itself show that it should work in rural locations beyond New Jersey. The disaggregate validation results show that the VULO method outperforms the alternatives at each density level. The steps in the VULO method ensure that the method correctly estimates block group average vehicle availability in every block group, as it contains an error correction term. Also, the expression for the error from the VULO method, Equation 4.15, includes no expressly location-related terms. The VULO method should be effective everywhere.

Chapter 5. Conclusions

This research lays out the methods and theoretical background for a new, practical method for developing context-sensitive residential parking standards. Literature on vehicle availability analysis indicates that the decision to own a given number of cars, and therefore require a given number of parking spaces, is influenced by a number of local factors: transit access, development density, on-street parking supply, housing prices, and others. Any system that neglects those influences is bound to make systematic errors in establishing adequate parking standards: requiring too much in some places and too little in others.

Unfortunately, parking standards are generally insensitive to the physical environment. Willson (2000) observes that planners are overwhelmingly inclined to use national parking standards or standards borrowed from nearby municipalities, rather than location- and project-sensitive standards. Therefore, current parking standards generally incorporate systematic biases. Willson (2000) further observes that parking regulators are more motivated to avoid the immediate costs of parking shortages than the indirect and often invisible (in the short term) costs of parking oversupply. That is, parking regulators are motivated to cope with the unknown errors in their methods by erring on the side of oversupply.

Assessing parking demand more accurately for a particular residential development promises to reduce oversupply. A more accurate assessment reduces uncertainty, weakens the case for safety factors, and reduces the magnitude of the safety factor (or additional term) necessary to give equivalent safety in the estimate. That is the aim of this research: to devise a method for producing more accurate projections of parking demand for a new project.

In addition, this research aims to make the new method practical—usable in the decision-making context. This adds significant constraints on the data and methods. For this research, a practical method is one that meets three criteria.

1. Inductive: The method should be rely heavily on observation.
2. Adequate & valuable: The method should process data in a scientifically sound way to create accurate estimates with low uncertainties.
3. Married to the decision process: The method should reflect the group decision-making context in which the resulting new standards will be used.

Together, these three criteria help ensure that the method can be understood, trusted and implemented.

First, a practical method must be principally inductive. Given that parties to the parking regulation process may bring different theories and technical sophistication to the decision-making forum, theory should be invoked only as necessary to generalize from data. Data, rather than theory, should form the principal basis of the method.

Second, a practical method must be scientifically sound and must result in accurate estimates. In Andrews's (2002) terms, it must be “adequate” and “valuable.” Any method that is not scientifically sound cannot be trusted to consistently transform measured data into valid estimates. Furthermore, the method must indeed produce accurate estimates to be worthwhile. That is, both the method's procedure and results must be trustworthy.

Third, a practical method must designed to fit within the decision-making context: it must be “married to the decision process.” For example, methods that draw on principles and data that are familiar to decision process participants are more likely to be readily accepted and incorporated. Methods that respect the participants' technical sophistication are more likely to be trusted. In contrast, methods that rely on alien language and abstruse theories face substantial obstacles to implementation.

In short, this research is aimed to develop a new, improved method for projecting the parking demand associated with a new residential development, a method that balances context sensitivity with practicality. It accomplishes that goal in three steps.

The first step is to identify the characteristics of the environment and local populations that influence parking demand. In Chapter 2 we argue that this is primarily a question of household vehicle availability, and we review the literature on vehicle availability analysis and prediction. Chapter 2 concludes by observing that although the demographic characteristics of household occupants are the dominant factors in household vehicle availability decisions, numerous locational factors combine to exert significant influence as well, especially development density, land-use mix and employment accessibility.

The second step is to devise a way to represent the factors identified above in parking standard regulations. Chapter 3 engages this task by addressing three subquestions. First, what development characteristics must be included when setting parking standards? A review of existing standards coupled with an analysis of household vehicle availability in New Jersey identifies unit type, bedrooms, and location as necessary and sufficient. Second, how do these regulation-appropriate variables relate to the predictor variables identified in Chapter 2? Regression analysis on 2000 Decennial Census PUMS data from north and central New Jersey shows that unit type, bedrooms, and location relate systematically to household composition and income. Third, what is the best way to express household location? An F test on a special tabulation of 2000 Decennial Census data in New Jersey shows that the block group, the smallest geographical unit at which vehicle availability data are publicly available, is preferable to the next larger option—the Census tract.

The final step in the research is to propose and test a method based on preceding lessons: this takes place in Chapter 4. The method is named Vehicles from Unit choice with a Location-based Offset, or the VULO method for short. The VULO method's first step entails regressing household vehicle availability on unit type and bedrooms, on a PUMA by PUMA basis. Second, these regression equations are employed to produce estimates of block-group average household vehicle availability. Third, the difference between reported and estimated average block group vehicle availability is identified as the location-based offset, and added to the PUMA-level regression to complete the estimate of household vehicle availability. This method uses the required variables, unit type, bedrooms and location, which are previously shown to relate directly and indirectly to vehicle availability. It defines location in terms of the block group. Finally, it uses only freely available data to create its estimates.

Chapter 4 concludes the research effort by demonstrating that the VULO method produces better estimates than alternatives in nearly all cases. Considering aggregate measures, the VULO method outperforms:

1. a statewide averages approach (akin to current practice in the Residential Site Improvement Standards in New Jersey) and
2. a PUMA-regressions method, which is approximately equivalent to the statewide averages approach implemented at the PUMA level instead.

Disaggregate validations show that the VULO method outperforms the statewide averages and PUMA-regressions approaches across practically all combinations of unit type and bedrooms at three block group densities.

By and large, this research has met its goal. It has produced a practical method for projecting the household vehicle availability, and therefore the majority of residential parking demand. It is practical in three senses. First, it is inductive, relying almost totally on Census data to create estimates. Second, it is scientifically sound—attending to previous work on estimating household vehicle availability—and more accurate than the alternatives. Third, it respects the decision process by using publicly available data and relying on commonly used housing characteristics. However, this work leaves important questions unanswered.

Future research

First, can we rationalize visitor parking standards as we have resident standards? Visitor parking requirements are a substantial portion of total residential parking requirements in some cases. For example, over 50% of New Jersey's parking requirement for 1-bedroom high rise apartments is due to visitor parking (State of New Jersey, 1997). For completeness, a method for establishing residential parking standards should address visitor parking as well as parking by residents.

Unfortunately, there is no widely measured proxy for visitor parking as there is for residents' parking. Visitor parking demands must be measured directly. At one end of the cost/accuracy spectrum, mail-back household surveys regarding the number and duration of visits hosted in the previous week, for example, would shed light on the question. In the most expensive and reliable approach, peak total (visitor + resident) parking demand could be measured by direct inspection. Either way, visitor parking data is expensive.

This suggests the need for a theoretically sound way to extend whatever scant data are available. Elsewhere we propose a stochastic model tuned to available data (Listokin, Walker, Ewing, Cuddy, & Cander, 2006). The model includes three parameters: likelihood of a resident being home in a given hour, the likelihood of having a visitor in a given hour, and the number of residential units sharing a parking lot. Figure 5.1 indicates the data fit assuming a 50% chance of a unit's resident parking at home and a 40% chance of having a visitor. The triangles, squares, and Xs are placed at the midpoints of ranges of development size, with the y-value indicating average measurements for rental and condominium townhouses and rental apartments. The model results are computed by simulating a 500-hour period five times and averaging the results hour by hour. The stochastic modeling approach appears promising, but it should be explored and validated with additional data.

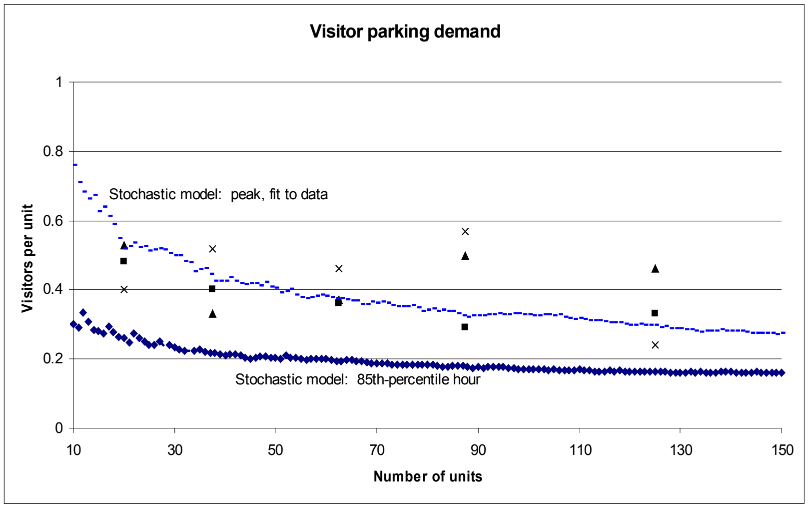

Figure 5.1. Stochastic visitor parking model results compared to tuning data
Source: Listokin et al., 2006: Chapter 9, Table 9.12

In particular, the influence of physical context should be considered. Just as residences in locations with good transit options and pedestrian access to jobs and services tend to host fewer automobiles, those residences have an increased chance of being visited by modes other than automobile. Even without any difference in visitation rates, which may well be related to, say, yard size, visitor parking demands should vary by location. Available data do not reflect that fact.

A second practical question bears on the VULO method's assumption that the proposed residential development in question is typical of the existing housing stock. Although this is an assumption typical of transportation planning in general—that historical trends continue into the future—it is problematic here. Controlling for bedrooms, unit type and location, new housing units are often more expensive than older units. The analysis that underlies New Jersey's RSIS accounts for this fact by considering only units constructed within the previous five years (State of New Jersey, 1997). However, the VULO method cannot operate under this constraint, because it unacceptably reduces the sample size for the foundational data while introducing an additional dimension, making the necessary aggregate block group-level data unavailable.

Thankfully, Equation 4.15, developed in Chapter 4 and restated below, allows this income bias to be reduced if not eliminated. The equation expresses the VULO method's errors in terms of PUMA-level regression results and differences between the residential development in question and the average characteristics of its block group.

$$E_{ij}=(u_{ij}-\bar{u}_j)(\gamma d_u+\lambda l_u)+(BR_{ij}-\bar{BR}_j)(\gamma d_B+\lambda l_B)+(D_{ij}-\bar{D}_j)(-\gamma)+\bar{\epsilon}_j-\epsilon_{ij} \quad (4.15)$$

D_{ij} is the set of household demographic characteristics that are assumed to influence vehicle availability. If that set is limited to household income, it is possible to estimate the income-related bias and correct for it. Doing this, however, requires an estimate of the incomes of future residents. The method for creating these estimates should be driven by rent or sale price projections; based on data on the relationship between income, other demographics, location, unit type, and bedrooms; informed by previous scholarly work on housing markets; and validated with data and by discussions with developers, who have their own methods for understanding their target markets.

On the more academic side, the theory presented in Chapter 2 suggests a warning and an opportunity for further research: household vehicle availability should be studied further in the context of parking supply. As depicted in Figure 2.2, the spatial distribution of on- and off-street parking supply influences a household's residential location and unit choice, which determines the on- and off-street parking supply available to the particular household. Therefore, a household's parking supply is to some extent driven by household demographics and attitudes, and by the household's location. Some combination of these factors also drive the vehicle availability decision. To what extent does parking supply independently influence vehicle availability? As its influence increases, independent of the demographic and locational factors that are associated with vehicle availability, so does the noise inherent in vehicle availability analyses that neglect parking supply. Appendix B indicates that off-street parking supply varies with location and unit choice, suggesting that parking supply's independent influence may be limited. A more rigorous analysis is appropriate to verify this suspicion and thereby test part of the working theory presented in Figure 2.2.

Implications

Despite these remaining questions, this research has significant potential to improve the practice of parking planning. First, the method can be used as intended: to evaluate and revise existing standards. It is methodologically straightforward, based on freely and publicly available data, and validated.

Second, this research demonstrates the value of changing reporting practices in the Census Transportation Planning Package. This set of special tabulations is designed to facilitate transportation planning. It includes a tabulation of vehicles available by unit type by number of residents in the household. However, residents per household is not nearly so constant in time as is number of bedrooms: unit type and bedrooms are essentially fixed properties of housing. Partly on that basis we have argued that these two variables are theoretically appropriate for linking housing stock to vehicle availability. Given that the first step in the four step planning process is to estimate trip generation rates (see Figure 2.1), usually by zone, and that zones contain a relatively stable distribution of housing, it would seem that the CTPP might better serve its intended purpose by tabulating vehicles available by unit type by bedrooms.

Even if not, the CTPP would certainly facilitate proper residential parking planning by including this new tabulation. As vehicle ownership is related to parking supply (which is related to parking standards), and vehicle use rates are related to vehicle ownership rates, changing the CTPP to support parking planning would also indirectly support transportation planning as well. Directly, indirectly, or both, adding this new tabulation to the CTPP would help it achieve its goals.

Third, this research establishes minimum requirements for future vehicle availability analyses. See Figure 2.2. It suggests first that household vehicle availability decisions must be considered in terms of the household demographics, the location of the household relative to transportation networks and activities such as jobs and services, and the type of housing unit inhabited. No dimension can be excluded.

Finally, the foregoing analysis of the uncertainty in residential parking demand should facilitate further discussion of the attitudinal and institutional barriers to more careful management of parking supplies. Traditional parking regulation practice is to err on the side of supplying excess parking. Under conditions of unknown parking demand and unknown uncertainty in the estimates thereof, fear of the immediate repercussions of parking shortages dominate the parking regulation process. This research presents methods for estimating the uncertainty in vehicle availability estimates, and explores the practical lower bounds on that uncertainty. Having estimated the quality of our knowledge of vehicle availability (and therefore the majority of residential parking demand), we are now prepared to ask how much uncertainty we will accept. To answer that question we must engage in values discussions: who benefits and who loses, in what ways and when, from parking excesses or shortages. These are important questions to address, and this research adds value by hastening them.

In sum, this research has been conducted to facilitate the improvement of residential parking regulation practice, through the development of a draft procedure for developing parking standards. In the process, it has raised questions about the limits of parking standards' precision and about how best to conceive of household vehicle availability decisions. It has the potential to advance the theory and practice of residential parking demand estimation.

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Appendix A. Modeling vehicle availability with categorical-variable methods

The literature review in Chapter 2 indicates that ordered response models (ordered logit or ordered probit) are increasingly chosen for vehicle availability analysis. It also presented evidence that multinomial logit models may be more appropriate for vehicle availability analysis than ordered response models. Early vehicle availability analysis used ordinary least squares approaches, but that approach was all but abandoned (until recently, as analysts use structural equation modeling to try to deal with endogeneities in travel behavior models).

Nonetheless, Chapter 3 uses ordinary least squares methods. This facilitates the identification of the direct and indirect relationships between residential choice variables and vehicle availability using an omitted variable bias framework. OLS fits the expository purpose of the regressions, but coefficient estimates from OLS on a categorical dependent variable may be biased and inefficient: using these coefficients to make inferences may be problematic. Any problems are mitigated by the fact that the VULO method proposed in this research does not rely on the regression coefficients except as guidance about the relationships among variables. This appendix confirms that the conclusions about those relationships drawn from the OLS models in Chapter 3 persist when the relationships are analyzed with a categorical modeling approach.

Table A.1 shows the results of an ordered logit analysis that is equivalent to the OLS results presented in Table 3.12. This is the full equation, where residential choice variables including unit type, bedrooms and location are used alongside their demographic covariates to explain variations in vehicle availability. The sample used here is the same as in Table 3.12 and described in Appendix : 115,349 households reported in the 2000 Decennial Census Public Use Microdata Samples in the 14 counties in New Jersey in the New York City commuter shed—north and central New Jersey.

Table A.1. Comparison of ordered response logit and ordinary least squares models

	ORL Est.	ORL SE	ORL Sig.	OLS Est.	OLS SE	OLS Sig.
SFD	1.424	.059	.000	.363	.022	.000
SFA	.989	.084	.000	.250	.032	.000
2 units	.657	.066	.000	.135	.025	.000
3-4 units	**.366**	**.070**	**.000**	**.041**	**.027**	**.122**
5-9 units	.353	.078	.000	.068	.030	.022
10-19 units	.465	.077	.000	.115	.029	.000
20-49 units	.271	.080	.001	.069	.030	.023
50+ units	0(a)	.	.	0(a)	.	.
[SFD] * BR	.281	.009	.000	.130	.004	.000
[single-family attached] * BR	.216	.026	.000	.086	.010	.000
[2 units] * BR	.356	.018	.000	.139	.007	.000
[3-4 units] * BR	.358	.026	.000	.137	.010	.000
[5-9 units] * BR	.304	.034	.000	.102	.013	.000
[10-19 units] * BR	.355	.038	.000	.112	.015	.000
[20-49 units] * BR	.454	.046	.000	.125	.018	.000
[50+ units] * BR	.598	.039	.000	.170	.015	.000
[SFD] * BR * density	-.080	.003	.000	-.032	.001	.000
[SFA] * BR * density	-.164	.009	.000	-.060	.003	.000
[2 units] * BR * density	-.169	.008	.000	-.060	.003	.000
[3-4 units] * BR * density	-.275	.012	.000	-.093	.005	.000
[5-9 units] * BR * density	-.379	.014	.000	-.125	.005	.000
[10-19 units] * BR * density	-.376	.017	.000	-.126	.007	.000
[20-49 units] * BR * density	-.409	.023	.000	-.120	.009	.000
[50+ units] * BR * density	-.307	.020	.000	-.092	.008	.000
Number of working adults	1.196	.008	.000	.424	.003	.000
Number of nonworking adults	.617	.008	.000	.216	.003	.000
Number of children	-.039	.006	.000	-.024	.002	.000
Household income (logarithm)	.601	.008	.000	.192	.003	.000

Note: The significance on the item in bold differs between the OLS and ORL models.

The different functional forms of OLS and ordered logit models make directly comparing the coefficients from the two models difficult. (This discussion follows Liao, 1994.) Ordinary least squares models directly estimate the dependent variable as a linear function of the independent variables. The coefficients are computed analytically so as to minimize the sum of squared differences between the estimates and the observed values of the dependent variable. See Equation A.1.

$$\hat{y} = \Sigma\, b_k\, x_k \quad \text{(A.1)}$$

An ordered logit model computes the probability of the dependent variable taking on a particular categorical value. That probability is computed by mapping the results of a latent linear equation onto a logistic (logit) probability distribution. (See Figure A.1.)

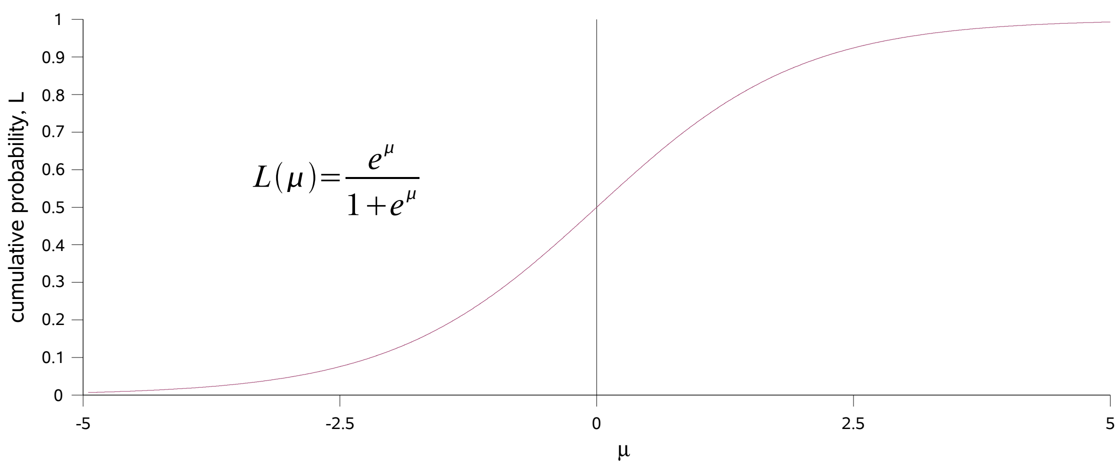

Figure A.1. Logistic cumulative probability distribution

The probability of residing in the jth category is estimated as

$$Prob(\,jth\,category) = L(\mu_j - \mu) - L(\mu_{(j-1)} - \mu) \quad \text{(A.2),}$$

where

$$\mu = \Sigma b_k x_k \quad \text{(A.3)},$$

$\mu_0 = -\infty$, $\mu_1 = 0$, and $\mu_J = 1$. Increasing values of μ lead to decreasing likelihood of residing in the first category and increasing likelihood of residing in the last category, all else being equal. The parameters in the model, the b_k and μ_j , are estimated via optimization routines to maximize the estimated likelihood of the observed distribution of dependent and independent variables.

Notwithstanding these differences, we can consider differences between coefficients *within* a given model, and can find a number of similarities on that basis. To put the comparison in the context of the dissertation research, we consider the observations made about the OLS results one by one. The comparisons in Table A.2 are based in the results in Table A.1. (Except as noted, differences are statistically significant.)

Table A.2. Comparing within-model observations from OLS and ORL models

	OLS	ORL
Single-family detached (SFD) units have higher VA than all attached units do, *ceteris paribus*.	☑	☑
Single-family attached (SFA) units have higher vehicle availability than do all other attached units, *ceteris paribus*.	☑	☑
Vehicle availability for units in 3- and 4-unit structures is not significantly greater than for units in 50 or more-unit structures.	☑	☒
For all unit types, increasing density decreases vehicles per bedroom.	☑	☑
Vehicles per bedroom is least sensitive to density for SFDs.	☑	☑
Vehicles per bedroom is less sensitive to density for SFAs and units in 3- and 4-unit buildings than for units in larger structures.	☑	☑
Increasing numbers of children weakly decreases VA, *ceteris paribus*, but the impact is insubstantial compared to workers or non-working adults.	☑	☑
Number of workers is about twice as influential on VA as is number of non-working adults.	☑	☑

It appears that using ordinary least squares rather than ordinal logit does not significantly distort the inferences drawn from the model in this research. Judging from Table A.2, the discussion in Chapter 3 would flow essentially as it does if ORL were used instead of OLS. This does not in any way repudiate categorical models or demonstrate the theoretical appropriateness of OLS models for any particular class of categorical questions. It merely confirms that the use of OLS here, in this case, is defensible on practical grounds. Any benefits accruing from the greater intuitiveness of OLS are not outweighed by accuracy costs.

Appendix B. Relating vehicle availability and off-street parking supply

Presumably, the availability of parking affects household's decisions on residential location and vehicle availability. This research uncovered no analyses of vehicle availability that explicitly considers parking availability. The work presented here represents an initial look at the relationship between housing choices, location choices, vehicle availability choices, and parking availability.

The American Housing Survey (AHS) includes the data to allow an analysis of on-street versus off-street parking. It asks household residents about the sort of off-street parking they have available to them: a garage, carport, driveway, lot or other included off-street parking. It also includes items on nearby parking lots and the number of household vehicles. Here we analyze the 2001 AHS for northern and central New Jersey. (See Appendix for a description of the population in the sample area. After removing nonresponses in key categories, this AHS sample includes 952 households.

The AHS locates responding households only to their Primary Metropolitan Statistical Area, which prevents direct assessment of local environmental variables' impacts. However, it includes a number of questions about the sorts of development that are within ½ block of the household. We use a number of these items in assessing the relationships between off-street parking availability, vehicle availability, location, and unit type.

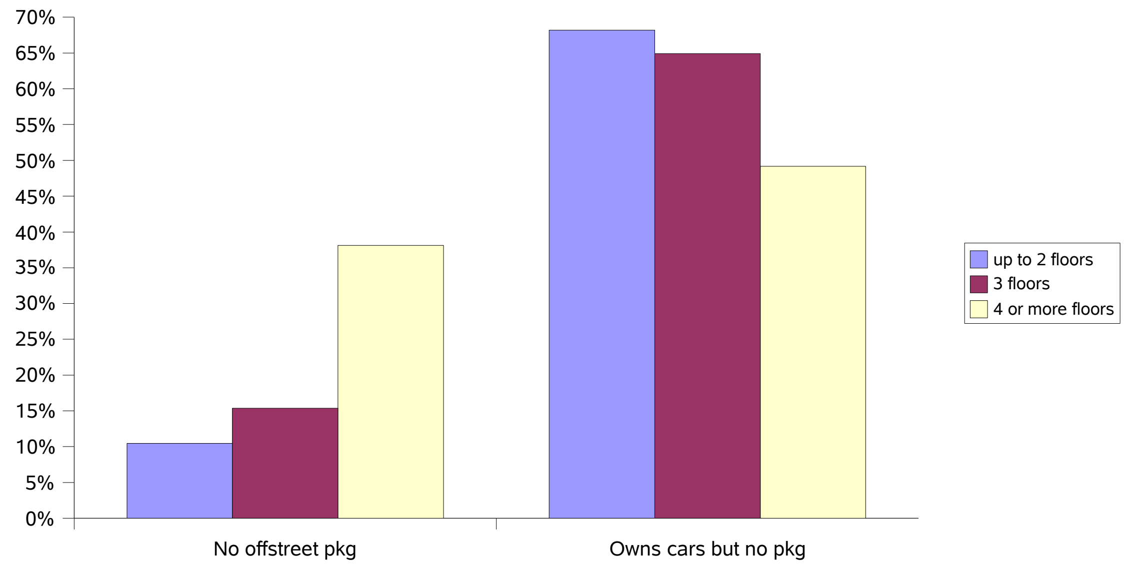

Figure B.1. Floors in building, off-street parking, and vehicle ownership ($N_{2floors}$=421, $N_{3floors}$=336, $N_{4floors}$=160)

The first density measure in the AHS is the number of floors in the resident's building. The first columns in Figure B.1 show that the fraction of the population with no off-street parking increases as the number of floors in the resident's building increases. Of all households in buildings with two or fewer floors, 10.5% have no off-street parking. That figure increases to 15.4% for three-story buildings, and 38.1% for buildings with four or more stories. The second set of columns shows the fractions of households without off-street parking that own at least one vehicle. That fraction decreases as the number of building stories increases: from 68.2% for up to two stories to 49.2% for four or more stories. Higher number of floors, which is a proxy for higher density, decreases off-street parking supply and the likelihood of parking on-street or in a lot.

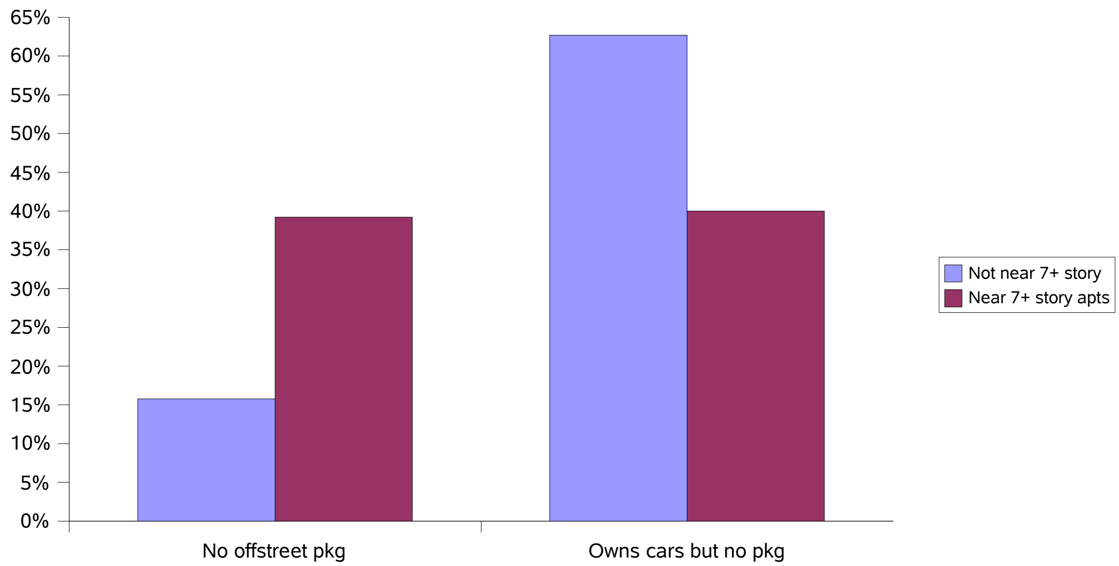

Figure B.2. Proximity to high-rise apartments, off-street parking, and vehicle ownership ($N_{not\text{-}near}$=901, N_{near}=51)

Figure B.2 shows how being within ½ block of apartment buildings with seven or more stories relates to parking availability and vehicle ownership. Having a high-rise apartment building nearby increases the likelihood of not having off-street parking available, from 15.8% to 39.2%. Given that a household has no off-street parking, being near a high-rise apartment reduces its likelihood of vehicle ownership from 62.7% to 40.0%. Being near a high-rise apartment building, which is a proxy for higher density, decreases off-street parking supply and the likelihood of parking on-street or in a lot.

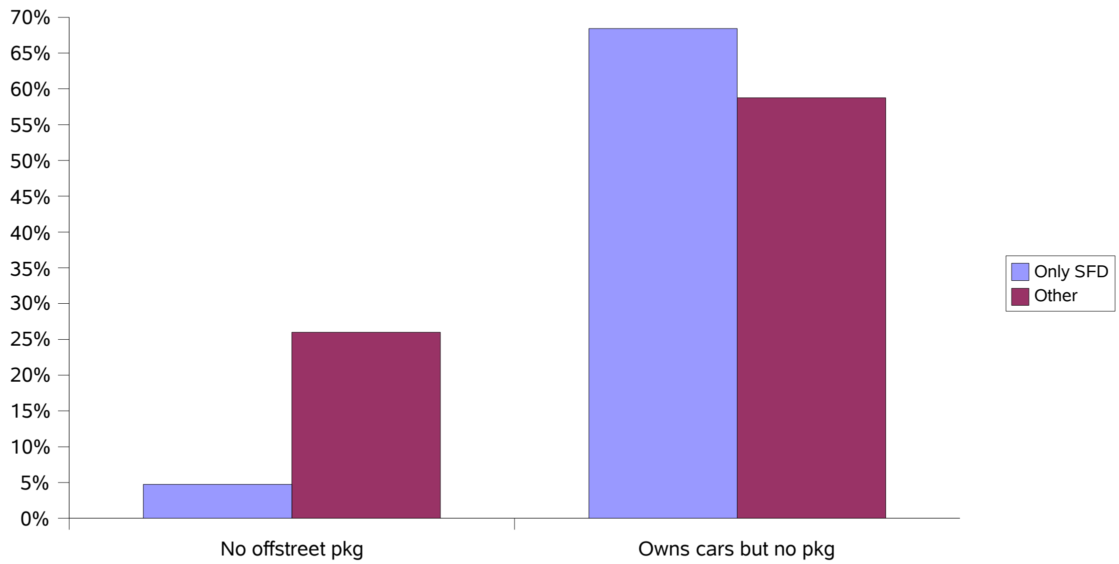

Figure B.3. Purely SFD neighborhood, off-street parking, and vehicle ownership (N_{SFD}=402, N_{other}=550)

Figure B.3 compares parking supply and vehicle ownership for two samples. The first has single-family detached (SFD) housing within ½ block, and no other type of land use within that radius. The second sample has at least one use type other than SFD within ½ block. Having uses other than SFDs nearby increases the likelihood of having no off-street parking, from 4.7% to 26.0%. It decreases the likelihood of owning a car, in the case where there is no off-street parking available, from 68.4% to 58.7%. Being near something other than purely SFDs, which is a proxy for higher density, decreases off-street parking supply and the likelihood of parking on-street or in a lot.

Figure B.4 indicates off-street parking supply and the use of non-off-street parking according to residential unit type. Generally, units in larger buildings are more likely to have no off-street parking available, and are less likely to have vehicles available to them in the event that there is no off-street parking.

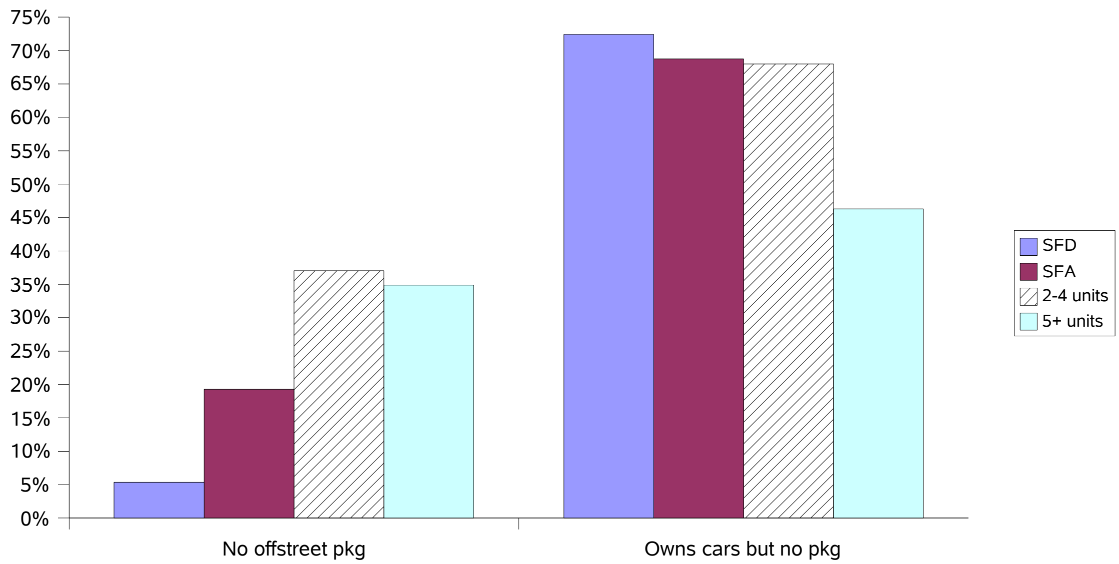

Figure B.4. Unit type, off-street parking, and vehicle ownership (N_{SFD}=542, N_{SFA}=83, $N_{2\text{-}4}$=135, N_{5+}=127)

Overall, these analyses suggest that households in more dense environments are less likely to have off-street parking available to them, and are less likely to own vehicles where there is no off-street parking. Aside from these trends, the analyses begin to explain the relationship between location, unit type, off-street parking availability, and the household vehicle ownership decision. The results also suggest that further analysis of off-street and other parking supply is warranted to relate vehicle availability analyses to residential parking standards. For example, Figure B.1 indicates that 15.4% of units in three-story buildings include no off-street parking, while 64.9% of those households (three stories without off-street parking) have vehicles available to them nonetheless.

Appendix C. The Decennial Census PUMS sample used in Chapter 3

The study area includes sparsely populated areas and a wide range of development forms. Table C.1 summarizes the sample we use to explore relationships among bedrooms, unit type and location.

Table C.1. Characteristics of the sample

	N	Mean	Std. Deviation
Vehicles available	116857	1.61	1.03
Bedrooms	116857	2.64	1.18
Number of working adults	116857	1.28	1.00
Number of nonworking adults	116857	0.80	0.86
Household income (1999)	116857	76849	76511
Population density (persons per square mile of land area in the household's PUMA)	116857	5163	6339

Relating density and unit type

Figure C.1 indicates the relationship between the fraction of the housing stock in detached housing and the density of an area. In the figure, each point represents one of the 6,510 block groups in New Jersey, whose average land area is 1.1 square miles and average population is 1,293 people. Denser areas tend to hold a higher fraction of multifamily units. All block groups with more than 14,606 residents per square mile of land have at least some attached housing.

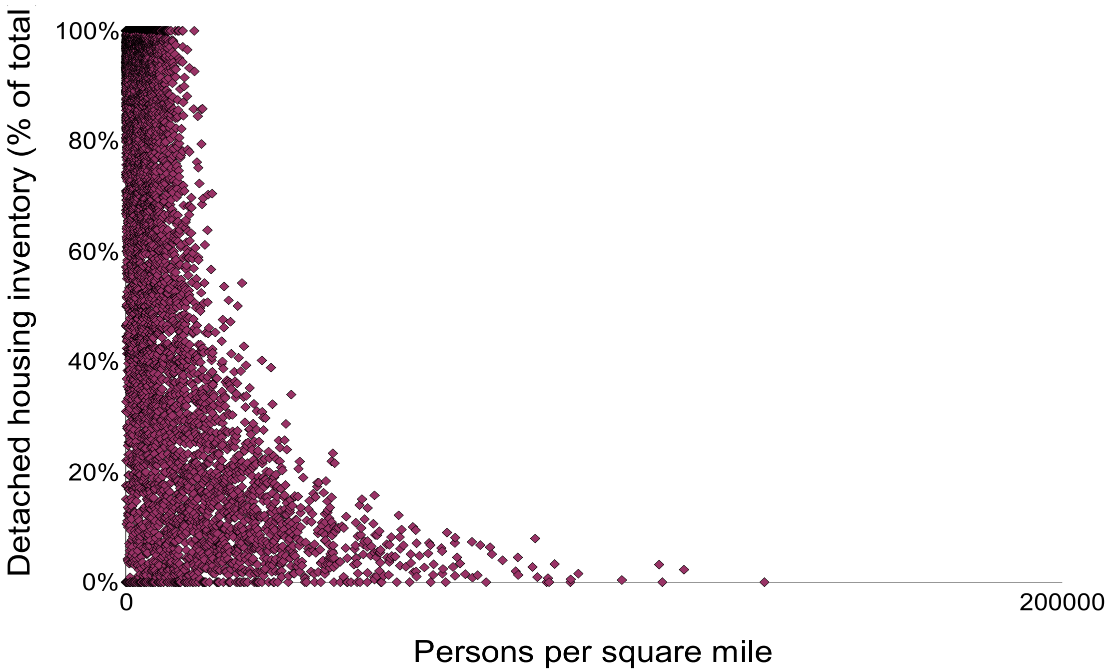

Figure C.1. Detached housing inventory as percentage of total by block group density

Relating bedrooms to density and unit type

Table C.2 indicates the association between household bedrooms, unit type, and density. Density is defined here as it is in the regressions in Chapter 3: it is a z-score of the natural logarithm of the PUMA density. Controlling for PUMA density, the average number of household bedrooms falls as the number of units in the building rises. Single-family detached units tend to have fewer bedrooms in PUMAs of higher density than they do in lower density PUMAs. Attached units in buildings containing as many as nine units show the opposite trend.

Table C.2. Bedrooms per household, r^2=0.442, N=116,857

Parameter	B	Std. Error	t
[Single family detached]	3.279	.004	882.938
[Single family attached]	2.461	.010	251.547
[2 units in struct.]	2.281	.009	246.932
[3-4 units in struct.]	1.759	.011	154.703
[5-9 units in struct.]	1.583	.013	126.392
[10-19 units in struct.]	1.377	.012	114.238
[20-49 units in struct.]	1.291	.016	79.025
[50+ units in struct.]	1.178	.013	89.202
[Single family detached] * density	-.025	.004	-6.410
[Single family attached] * density	.093	.010	9.254
[2 units in struct.] * density	.090	.009	10.088
[3-4 units in struct.] * density	.161	.010	16.143
[5-9 units in struct.] * density	.036	.011	3.305
[10-19 units in struct.] * density	-.009	.012	-.795
[20-49 units in struct.] * density	.022	.015	1.435
[50+ units in struct.] * density	.017	.012	1.424

Appendix D. Example of the VULO method

This appendix clarifies the VULO method developed in this research by executing the method on a sample development. Consider a 200-unit residential complex, containing 72 1-BR units and 128 2-BR units, proposed in South Orange, New Jersey. It lies in the 2000 Decennial Census 5% Public Use Microdata Area (PUMA) 1402, Essex County, Tract 193, Block group 3. The detailed steps in estimating the average vehicle availability for the units in this new development are presented below.

Step 1: Regress vehicles on unit type and bedrooms at the PUMA

The 2000 Decennial Census 5% Public Use Microdata Sample (PUMS) for PUMA 1402 contains 1,906 responding households distributed among the four unit types as shown in Table D.1.

Table D.1. Households by unit type in PUMA 1402

Unit type	N
SFD	514
SFA	53
2- to 4-fam	509
5+ fam	830

Table D.2 presents the regression coefficients used to estimate household vehicles for all households in PUMA 1402. Spelled out, the equation is:

$$v = 0.393 + 0.177 * BR + 0.587 * dummy_{SFD} + 0.319 * dummy_{SFA} + 0.257 * dummy_{2to4} \quad \text{(D.1)}.$$

It can also be expressed in tabular form, as shown in Table D.3.

Table D.2. Household regression: vehicles on bedrooms and unit type

Parameter	B	Std. Error	Sig.	95% Confidence Interval	
Intercept	.393	.039	.000	.317	.469
Bedrooms	.177	.020	.000	.138	.216
SFD	.587	.068	.000	.454	.720
SFA	.319	.124	.010	.075	.563
2-4 units	.257	.053	.000	.153	.361
5+ units	0(a)	.	.	.	.

a This parameter is set to zero because it is redundant.

Table D.3. Household vehicles by bedrooms and unit type

	Bedrooms				
Unit type	0	1	2	3	4+
SFD	0.98	1.16	1.33	1.51	1.69
SFA	0.71	0.89	1.07	1.24	1.42
2-4 units	0.65	0.83	1.00	1.18	1.36
5+ units	0.39	0.57	0.75	0.92	1.10

Step 2: Estimate average vehicles per household at the block group

According to the 2000 Decennial Census Summary File 3 (SF3), the block group in question, Block Group 3 in Census Tract 193 in Essex County, New Jersey, has the characteristics listed in Table D.4. Although SF3 reports 317 households in this block group, the 1-in-6 sampling density indicates that approximately 53 households actually responded to the long form questionnaire.

Table D.4. Block group characteristics, N=317

Average Bedrooms per HH	Fraction of HH that are				Average vehicles per HH
	SFD	SFA	2-4 units	5+ units	
3.40	0.79	0	0.21	0	1.60

In Step 2, we estimate the block group average household vehicle availability by populating Equation D.1 with the block group average characteristics in Table D.4. The dummy variables, when averaged over the block group, become the fraction of households in each unit type class. The result is

$$v = 0.393 + 0.177 * 3.40 + 0.587 * 0.79 + 0.319 * 0 + 0.257 * 0.21 = 1.51 \quad .$$

Step 3: Compute and apply the local offset

The local offset is the difference between the measured block-group average vehicle availability, 1.60, and the estimated value, 1.51. The measured value reflects the actual vehicle ownership decisions made by the households in the given block group, including the influences of their demographics and their location in the land-use and transportation context. By contrast, the estimated value is driven by the demographics of the entire PUMA, and the household-average locational effects on all households in the PUMA. The difference, 0.09, is a measure of the systematic differences between the block group and the PUMA. Controlling bedrooms and unit type, the block group in question tends to have higher average household vehicle availability than the PUMA—the average difference is 0.09 vehicles per household.

Adding the location-based offset to the equation from Step 1, Equation D.1, results in the following final estimate:

$$v = 0.393 + 0.177 * BR + 0.587 * dummy_{SFD} \quad \text{(D.2)}$$

$$+0.319*dummy_{SFA}+0.257*dummy_{2to4}+0.09$$

In our case, we have 1- and 2-BR units in a building with more than five units. All dummy variables equal zero. For the 1-BR units, we estimate 0.393 + 0.177 + 0.09 = 0.66 vehicles per household. For the 2-BR units, we compute 0.393 + 0.177 * 2 + 0.09 = 0.84 vehicles per household. As the development contains 72 1-BR units and 128 2-BR units, the total estimate is 72*0.66 + 128*0.84 = 155.0 vehicles owned.

Curriculum Vita

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Education

1988 – 1992	Cornell University
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Publications

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