

BIDDING FOR PARKING:

The Impact of University Affiliation on Predicting Bid Values in
Dutch Auctions of On-Campus Parking Permits

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Table of Contents

I. Introduction	5
II. Literature Review	9
A. Pricing Mechanisms	9
B. Mode Shifting Behavior	11
III. Theory.....	13
A. Common Auction Mechanisms	14
B. Multi-Unit Auctions.....	15
C. Discriminatory vs. Uniform Price.....	16
IV. Data	18
A. Auction Data Introduction	19
B. Auction Summary Statistics.....	22
C. Demographic Information.....	23
V. Empirical Specification	25
A. Bid Timing	25
B. Supply and Demand	27
C. Clustering.....	30
D. Regression Analysis.....	39
VI. Conclusion.....	43
VII. References.....	46
VIII. Appendix.....	50

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Abstract

Parking is often underpriced and expanding its capacity is expensive; universities need a better way of reducing congestion outside of building costly parking garages. Demand based pricing mechanisms, such as auctions, offer a possible solution to the problem by promising to reduce parking at peak times. However, faculty, students, and staff at universities have systematically different parking needs, leading to different parking valuations. In this study, I determine the impact university affiliation has on predicting bid values cast in three Dutch Auctions of on-campus parking permits sold at Chapman University in Fall 2010. Using clustering techniques crosschecked with university demographic information to detect affiliation groups, I ran a log-linear regression, finding that university affiliation had a larger effect on bid amount than on lot location and fraction of auction duration. Generally, faculty were predicted to have higher bids whereas students were predicted to have lower bids.

JEL classification: C38; C57; D44; R4; R49

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I. Introduction

It is no secret that managing parking at a university is a difficult task. Often limited by space and budget, a parking administration is recurrently forced to make difficult and unpopular decisions in order to appropriately allocate parking for a community of faculty, students, staff, and visitors. While nobody enjoys dealing with parking, it is an issue of high importance. At universities, parking generally ranks low on satisfaction for all members of the organization. Parking is also a limited resource that can be very costly. For example, Duke University spends an estimated \$20 million each year on its parking accommodations (Cavanaugh, 2013). Furthermore, congestion created by a lack of parking is an issue that affects drivers and non-drivers alike. Some studies have found that in particularly congested urban areas, up to 30-percent of drivers were cruising for parking spaces (Shoup, 2006). As universities grow, parking demand only increases, further exaggerating congestion and emissions problems.

A common approach universities take when facing the problem of insufficient parking accommodations is to increase the parking supply. However, expanding the number of parking spaces on campus can be extremely expensive, with the cost of fresh spaces in new garages often exceeding the value of the cars residing within them (Shoup, 2008). Furthermore, solely expanding the parking supply prolongs existing pricing and allocative inefficiencies. Average cost pricing, which is used by many university administrators to cover the substantial costs of operating and maintaining parking facilities, does not consider consumer demand in setting prices. Additionally, common parking allocation structures, which include lotteries, waiting lists, first-come, first-served policies, and need-based solutions, are often political in nature and do not deliver parking to those who value it most (Shoup, 2008). For example, at The University of California at Los Angeles, Nobel laureates are often given the best parking spots on campus

without any consideration of their parking valuations, needs, or preferences. Students, meanwhile, are awarded parking spaces based on commute length, leading many students to outwit the allocation system by duplicitously listing a home address of a parent, sometimes hundreds of miles away, in order to get a better space. More generally, parking is typically priced based on university affiliation, defined here to refer to whether an individual is faculty, staff, or a student, where those paying more for parking are not necessarily those who value it the most. In an extreme example, The University of North Carolina at Chapel Hill prices parking for faculty based on salary information, with more highly paid faculty in some cases paying over two times more than other professors for equivalent spaces (Appendix, Figure I-A). In other schools, prices vary by lot location, where permits are restricted to different groups of affiliates (i.e. a faculty lot vs. a student lot).

The immense cost of increasing the parking supply, along with the inherent inefficiencies of traditional parking permit pricing schemes and allocation structures, have led some economists to argue that reducing consumer demand is a cheaper and more powerful solution to many parking and congestion issues. The case for demand based parking can be easily illustrated by walking around a busy parking lot at different times of the day. Even in the most congested of parking lots, a large number of spaces are usually open outside of peak times of activity. Demand based parking strategies seek to provide incentives for parkers to park at times of less activity, potentially solving congestion issues without increasing the parking supply (Shoup, 2008). One proposed idea, aptly named “The Goldilocks Principle”, suggests that prices should constantly be nudged up or down until the demand is “just right” (i.e. adjust the price of permits until supply is slightly greater than demand) (Shoup, 2008). However, this strategy does not differentiate between individuals’ parking valuations, leaving room for improvement.

Going a step further, auctions provide a higher level of granularity, allowing an administration to directly price parking based on demand, delivering spaces to those with the highest valuations.

Ideally, economic theory suggests that auctions yield promising results in reducing congestion. However, few universities have attempted to price parking using auctions due to uncertainties about their effects on parking populations. While it is well documented that individuals across university affiliations react differently to parking price increases (Shannon et al., 2006; Whalen, Páez, & Carrasco, 2013), it is unclear whether or not a demand-based parking system would favor one group over another. In order to maximize social benefit, a planner would want to know the degree to which individuals' affiliation with a university affects their bid values because different university affiliates have varying schedules, translating into distinct commuting needs. For this reason, in this study, I will explore the relationship between particular auction-based permit pricing schemes and university affiliation in order to best understand the effects auctions have on these groups of individuals and to better price parking in the future, reducing congestion while not compromising daily university operations.

There are two main strands of relevant parking literature that focus on (1) exploring demand-based parking structures and (2) determining the biggest factors that influence consumers' mode shifting behavior, which is defined here as consumers' propensity to switch their primary mode of transportation when commuting due to economic constraints. While mode shifting behavior is not the subject of this study, much of the research in evaluating the subject focuses on understanding differences in parking preferences across distinct groups of parkers. This project works to understand how willingness to pay for parking varies across affiliations. I make a meaningful contribution to the literature by focusing on using university

affiliation to predict bids cast in Dutch Auctions, a format characterized by its reversed highest bid and open bidding, where a high price is steadily reduced until a bid is made, making for a quick and efficient sale. Of the studies that examine the differences in willingness to pay for parking permits among university affiliates, none explore these differences using auction data.

In this study, I analyze a unique dataset from Chapman University, containing data from three Dutch Auctions used to allocate parking permits for on-campus spaces in Fall 2010. Using this resource, I determine the impact university affiliation has on predicting bid values. Using clustering techniques crosschecked with demographic information to identify student, faculty, and staff groups within the auction data, I find that university affiliation has a larger impact on bid amount than lot location and fraction of auction duration. Generally, faculty were predicted to cast higher bids whereas students were predicted to cast lower bids. These results suggest the importance of university affiliation when planning an auction of parking permits. Implications of this study surpass the scope of the individual university. In many ways, large universities resemble small cities. Findings from this research can also have policy implications for cities. Additionally, implications about consumers' willingness to pay, price elasticities, and potential benefits of pricing structures can be applied to other areas, such as parking at corporate headquarters, office complexes, cities, and other public areas.

In Section II, I review the existing literature relevant to mode shifting behavior and demand-based pricing. I describe the relevant economic theory, focused on auctions, in Section III. In Section IV, I provide an overview of the parking and auction data from Chapman University. In Section V, I present an empirical specification and analyze the results. Section VI concludes the paper.

II. Literature Review

There are two relevant strands of research on the subject of parking with regards to this paper. One strand of literature focuses on determining ideal pricing mechanisms used in a variety of parking systems (Buchanan, Gjerstad, & Porter, 2012; Shoup, 1997, 2008). The second strand of literature explores which factors have an impact on consumers' mode shifting behavior, in order to understand what causes consumers to switch their primary mode of transportation (Jou, Hensher, Liu, & Chiu, 2010; Shannon et al., 2006; Sultana, 2015; Vega & Reynolds-Feighan, 2009; Whalen et al., 2013). However, there is a notable gap in the existing research regarding the impact of using auctions to price parking between groups of parkers varying by university affiliation.

A. Pricing Mechanisms

Much of the existing research on parking focuses on explaining its high cost and providing policy recommendations. The core of the problem begins with the high cost of underpriced parking. Parking is typically a problem when there is low supply and high demand, resulting in congestion and wasted fuel and time in parking space searches. Parking expert, Donald Shoup, has written extensively about the high cost of free parking, calculating high valuations for individual parking spaces (1997). For example, at UCLA, Shoup calculated that new parking spaces, created by the construction of new parking garages, cost the university between \$9,000 and \$23,000 per space. Factoring in the additional amortization and maintenance costs over the fifty year life of the parking space, many of the spaces had higher costs than the vehicles that occupied them. Because of the high cost of parking and because parking is often underpriced, it is essentially a tragedy of the commons problem, where an over availability of free parking is met with unrelenting demand.

After providing evidence for the high cost of developing new parking spaces, Shoup (1997) argues that parking should be priced in a way that passes the costs of the resource directly to those who use it. Shoup criticizes minimum parking requirements, which are essentially regulations that mandate a certain number of parking spaces for a particular unit of commercial space or housing, stating that such requirements create artificial subsidies for parkers. He argues that when organizations are required by governments to build more parking spaces, they incur additional building expenses related to the construction of new parking facilities. These expenses are passed on to rent payers and tenants, thereby creating an artificial subsidy for parkers. He concludes that minimum parking requirements should be eliminated in favor of market prices in order to improve efficiency. This research provides motivation for the research question at hand by identifying problems with traditional parking pricing structures and offering policy advice based in economic theory. However, the study merely suggests the elimination of minimum parking requirements and does not further explore alternative pricing structures that are rooted in economics, such as auctions.

In order to better recover the high cost of creating additional parking spaces, some researchers have suggested to let the prices do the planning. For example, other papers have attempted to make a case for using demand to set parking prices at universities by calculating the opportunity cost of building more parking on universities' campuses. Shoup (2003) provides a thorough analysis of existing parking structures for the UCLA campus in southern California, demonstrating (with humor) how political pricing mechanisms such as lotteries, waiting lists, selection by seniority, need-based selection, and first-come, first-served mechanisms do not capture consumer demand and therefore cause inefficiencies. For example, on the UCLA campus, students often bend the rules when filling out their parking applications by listing the

address of their parents, representing a commute that a considerable distance from the university, in order to increase individuals' perceived parking priority in the eyes of the UCLA administrators. Additionally, Shoup makes a case for using demand-based prices to reduce the number of parkers at times of peak demand due to the extraordinarily high opportunity cost of creating additional parking spaces on campus. One proposed solution, dubbed "The Goldilocks Principle", suggests setting the price of parking based on consumer demand, such that an equilibrium with 15-percent space availability is created. This "just right" value can be found by increasing the price of parking until demand is reduced. This study is of extraordinary value to the research at hand due to the fact that it lays the frameworks for demand-based pricing of parking at a university. However, this study does not explore or forecast the possible effects auctions might play on different individuals or consider the how demand might vary dependently or independently of university affiliation.

B. Mode Shifting Behavior

Observations from research on mode shifting behavior, particularly those relating to affiliates' willingness to pay for parking, provide key insight on how groups of individuals value parking differently. In addition to increasing parking fees, universities attempt to reduce congestion by encouraging alternative forms of transportation. There is a wealth of research available based on predicting consumers' mode shifting behavior. A wide number of studies focus on the factors that determine consumers' mode shifting behavior, or willingness to switch from car-based transportation solutions to alternative transportation solutions, with papers focusing on both cities (Jou et al., 2010; Vega & Reynolds-Feighan, 2009) and universities (Shannon et al., 2006; Sultana, 2015; Whalen et al., 2013). Elasticity of demand and marginal willingness to pay are the primary metrics employed by a variety of papers when predicting

consumer mode shifting behavior. Different studies have found that mode shifting depends on an assortment of factors such as travel time (Whalen et al., 2013), cost (Sultana, 2015; Whalen et al., 2013), daily car use habits, car ownership (Sultana, 2015), and perceived travel time by method of transport (Shannon et al., 2006; Sultana, 2015; Whalen et al., 2013). Other important factors include the presence of convenient nearby housing (Shannon et al., 2006), availability of empty campus parking spaces (Sultana, 2015), subsidized public transportation with clear and readily available time tables (Shannon et al., 2006), travel time by bike and car (Whalen et al., 2013), and street and sidewalk density (Whalen et al., 2013). In some studies, factors such as race, gender, income, ethnicity, and environmental concerns were conversely shown to not have a large effect on student's decision to purchase a permit (Sultana, 2015).

Socio-economic factors were also found to affect consumers' decisions to purchase parking passes in universities and cities (Sultana, 2015; Zhou, 2012). For example, analysis involving a cross logistic regression of data gathered through a web-based survey consisting of 2253 undergraduates at the University of North Carolina at Greensboro, designed to determine factors that led students to purchase parking permits, concluded that car-ownership and daily use habits explained students permit purchase decisions, whereas other factors, such as income, race, and gender were of little significance (Sultana, 2015). However, in another study, socio-economic factors linked to housing location, central vs. non central commuting patterns were also found to be significant in determining individuals' willingness to pay for parking (Vega & Reynolds-Feighan, 2009).

Studies examining the differences in willingness to pay between university students, faculty, and staff are extremely relevant to this study. In one such study, students were found to have higher willingness to pay for parking than faculty and staff, a conclusion justified in part

by the systematically different commuting needs among students, faculty and staff (Lipscomb & Koford, 2011). A key contribution to the literature was the necessary distinction between faculty, staff, visitors, and students when examining price elasticities. The study implies that different pricing strategies could be used on different groups in order to most efficiently optimize and reduce the number of cars on campus. This study confirms the legitimacy of the research question. If differences in willingness to pay vary widely between faculty, staff, students, and visitors, it is possible that these systematic differences in preferences are good predictors of bid values in an auction environment, indicating a policy that may or may not maximize social benefit.

In review, previous studies have concentrated either on understanding what drives mode shifting behavior, addressing both universities and cities, or on optimizing parking efficiency through pricing structures driven by economics, such as demand-based pricing. This study differentiates itself by evaluating the effectiveness of using university affiliation to predict bid values cast in auctions designed to sell parking permits at a university.

III. Theory

The primary economic theory that informs this study relates to auctions. Auctions are ubiquitous across markets and have served important allocative roles for thousands of years. Auctions are used when there is an asymmetry of information between the seller and potential buyers. The seller usually knows very little about the valuations of the buyers and the buyers have no incentive to inform the seller about their valuations. Therefore, auction mechanisms are designed to elicit information about potential buyers' valuations of particular objects. (Paarsch & Hong, 2006, pp. 2-3). In this section, I present a categorization matrix of common auction

mechanisms, introduce a model for describing bid allocation in multi-unit auctions, and explain different auction pricing mechanisms.

A. Common Auction Mechanisms

Auction mechanisms are designed to elicit different types of information between bidders and the seller. Hendricks & Porter explain that auction mechanisms are differentiated by the way information is sent to the bidders and by the seller’s allocation rule, which dictates the probability a bidder receives an item and which bidder might receive an item depending upon the bids received (2007). There are four common groupings of auctions: Dutch, First Price Sealed Bid, English, and Vickrey (Second Price Sealed Bid). These categories are differentiated by whether the auctions are open or closed and by whether payments are equal to the Highest Bid or Second Highest Bid. The corresponding categorization matrix is presented below (Table III-A).

Table III-A: Common Auction Mechanisms

	Highest Bid	Second Highest Bid
Open	Dutch	English
Closed	FPSB ^a	Vickrey (SPSB ^b)

^aNote: FPSB is an acronym for First Price Sealed Bid

^bNote: SPSB is an acronym for Second Price Sealed Bid

In open auctions, bids are known to all parties and are announced in a sequence. In a Dutch Auction, the “asking” or initial price is set at a high value and is lowered by the seller until a bid is offered (i.e. when a bidder says “stop!”). The first bidder wins the item at the stop price (the reduced asking price at the time of the stop), leaving only one winning bid submitted in single-unit auctions. The alternative is an English Auction, where the seller incrementally increased the price until no further bids are made. The bidder with the highest bid wins the

item at the second highest bid price. Closed auctions consist of n -bids from n -bidders to be considered simultaneously by the seller. An object in a First Price Sealed Bid Auction is awarded to the highest bidder who pays their own bid price. This is in contrast with the Second Price Sealed Bid Auction, where the highest bidder pays the highest losing bid price. These formats have countless variations which can be further differentiated by the inclusion of minimum bids, entry fees, reserve prices, and subsidies (Hendricks & Porter, 2007).

B. Multi-Unit Auctions

When distributed in large quantities, items like parking spaces can be sold in multi-unit auctions. To be considered a multi-unit auction, the items to be sold should match one of the following three descriptions: (1) physically identical items, such as identical bottles of wine or equivalent treasury bills, (2) items that are distinct but still good substitutes, such as parking spaces drawn from the same lot, or (3) identical items that have a higher value when more are obtained, such as a collection of stamps. While multi-unit auctions are a natural extension to the auction mechanisms discussed prior (Figure III-A), there are additional complexities to consider in their modeling and interpretation.

Formally, in a multi-unit auction, K identical items are auctioned off to i bidders who each submit k^i bids, where each $k^i \leq K$. A bidder is asked to submit k bids b_k^i , where $b_1^i \geq b_2^i \geq \dots \geq b_k^i$, such that b_1^i is the amount *Bidder* i is willing to pay for one unit, $b_1^i + b_2^i$ is the amount *Bidder* i is willing to pay for two units, and so on (Krishna, 2002, p. 166). A bid vector is defined as $b^i = (b_1^i, b_2^i, \dots, b_k^i)$.

The allocation rule for multi-unit auctions varies from single-unit auctions, but follows conventional principles of supply and demand. Considering each bidder's individual bid vector, aggregate demand is generated by horizontally adding the bid vectors. As an example,

consider the following three bid vectors for three identical objects ($K=3$):

$$b^1 = (9, 7, 1) \tag{1}$$

$$b^2 = (8, 3, 2) \tag{2}$$

$$b^3 = (6, 5, 4) \tag{3}$$

In this situation, the three highest bids are (b_1^1, b_1^2, b_1^3) , corresponding to $(9, 8, 7)$, where *Bidder 1* is sold two units, *Bidder 2* is sold one unit, and *Bidder 3* is sold zero units. More generally, if *Bidder i* has $k \leq K$ of the K highest bids, then *Bidder i* is awarded k units. Supply is fixed at K and is represented by a vertical line. All bids to the left of K (the K highest bids) are considered winning and the number of units distributed to each bidder is equal to the number of winning bids cast by the bidder.

Formally, in a Dutch Auction, there are K units available to N bidders, where $N > K$, operating under the assumption that demand is greater than supply. Every buyer values the good at a value v . A value v is drawn from a group that is independently and identically distributed. Maximum and minimum values for the distribution are bounded by the set $[a, b]$. The initial “asking price” P_{ask} is set high to the end of the value distribution at b . With each tick of the auction clock, the price is lowered by a value e . Once the auction begins, the price P is $(b - ze)$ for z ticks of the clock. When the first bidder stops the clock, they accept the current clock price, leaving $m-1$ units remaining. The process continues until the number of unit remaining reaches zero (Buchanan et al., 2012; Paarsch & Hong, 2006).

C. Discriminatory vs. Uniform Price

While the allocation rule described above is standard across a variety of multi-unit auction types, the amount paid by winning bidders depends on the specified pricing rule. The two most relevant (and common) pricing rules to this study are Uniform-Price and

Discriminatory Prices. Because the auction data used in this study represent Uniform-Price Auctions, Discriminatory Prices are only briefly overviewed to provide contrast.

In a Discriminatory Auction, a bidder pays the amount equal to the sum of their bids deemed as winning, representing a case of perfect price discrimination. It is important to note that Discriminatory Auctions do not necessarily raise more revenue than other auctions with different pricing mechanisms, as explained by their equilibrium bidding behavior (Krishna, 2002, p. 168).

In a Uniform Price Auction, all K units are sold at a market clearing price, which is defined loosely as either the highest losing bid or the lowest winning bid, where the total amount demanded is equal to the total units supplied. Let C^i be the K vector of bids that *Bidder i* is competing with. The competing $K(N-1)$ bids b_k^j , where N equals the total number of bidders and $i \neq j$, selecting the first K bids, form the bid vector, representing all bids in competition with *Bidder i*. Here, C_1^i is the highest competing bid, C_2^i is the second highest competition bid, and so on. The number of units won by *Bidder i* is equal to the number of competing bids beaten (Krishna, 2002, p. 170). The market clearing price is set as the highest losing bid. A winning *Bidder i*, winning k^i units, pays $(k^i * p)$, where p equals the market clearing price. When only one unit is for sale ($K = 1$), a uniform price auction reduces to a second-price sealed bid auction (Krishna, 2002, p. 170).

Whether goods being sold in an auction have common or private values has major implications on bidders' dominant strategies (Hortaçsu & McAdams, 2010). Private values occur when bidders know their own valuation of an object with certainty but do not know the extent to which the object is valued by others. This is usually the case when the value of a good is derived from its consumption. If bidders value a good on the basis of how much the item will

generate in resale, the good may be better defined as a common value good. Parking is clearly a private value good due to the fact that individuals generally do not update their valuations for a parking space once they see what others are willing to pay for it. Whether individuals update what they are willing to pay in response to seeing what others are willing to pay is a different matter. It is possible to identify common value goods by testing for a winner's curse. Outlined by theory proposed by Milgrom and Weber (1982), the likelihood of a winner's curse increases as the number of bidders increase. However, in a private value auction, the increase in the number of bidders should not change drastically due to the fact that in such situations, theory suggests that the dominant strategy for bidders is to bid their true valuations (Paarsch & Hong, 2006). In Uniform-Price multi-unit auctions, the fact that bidders are incentivized to bid their true valuations, is of key importance to the relevance of the empirical results in this study.

IV. Data

Data for this project consists of a unique dataset containing three parking permit auctions held in Fall 2010 at Chapman University and publicly available human resources reports and demographic information for Chapman University between 2010 and 2011 from the U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. The auction data were generously provided by Dr. David Porter, a professor of economics at Chapman University, and Charlie Schaezlein, a former research assistant of Dr. Porter, who first introduced me to these parking auctions at Chapman. Specific information explaining the auction process used is outlined in a paper by Buchanan, Gjerstad, and Porter which explores information effects in multi-unit Dutch Auctions (2012). This paper is the only published work derived from this dataset known to this researcher. Documentation for the human resources reports and demographic reports for Chapman University 2010-2011 can be

accessed on the Integrated Postsecondary Education Data System (IPEDS) section of the website for the National Center for Education Statistics.

A. Auction Data Introduction

By the late 2000's, Chapman University was plagued with parking and congestion problems, generating a substantial body of criticism among individuals associated with the university. Located in Orange, California, only a 45 minute drive away from car-centric Los Angeles, driving has long been a major concern for students, faculty, and staff alike, with an estimated 85-percent of the 6881 undergraduate students owning a car in 2010. In an attempt to solve this problem and address the criticism, a team was assembled consisting of members from the school's administration and economics department in order to create more open spaces at times of peak traffic (Horn, 2014). The team attempted to solve this problem, in part, by selling permits using online reverse (Dutch) auctions. While the team did not generate more open parking spaces by reducing the demand, they were able to perform a fascinating experiment in which they attempted to allocate existing spaces to those who valued them at the highest level.

While Chapman conducted auctions for various reserved and non-reserved on-campus lot permits each semester between 2009 and 2011, the dataset acquired only contains three auctions held in the fall of 2010. Two types of permits were sold in these auctions: (1) permits for a limited number of reserved parking spaces; and, (2) permits for spots in an on-campus lot with a low permit to slot ratio. Auctions for reserved spaces were conducted annually whereas auctions for on-campus lots were held each semester. Permits were sold in the lots Argyros, Reserved, and Villa Orchard (Appendix, Figure IV-A). These auctions, on average, lasted about eight days each. Despite being conducted simultaneously, the auctions for Reserved and Villa Orchard permits were separate. The auction for the Argyros lot permits was held subsequently

at a later date. All auctions in the dataset took the form of a reverse (Dutch) auction, where bids started high and were subsequently lowered by a constant rate per time interval until reaching a minimum price. Bidders in all auctions paid the market clearing price (which in almost all cases was lower than their bid value). In for my empirical analysis to be economically interpretable, it is essential that the bids cast in these Dutch auctions are equal to the valuations of the bidders casting them. According to the relevant theory, assuming that parking is of private value, bidders paying a uniform price are indeed incentivized to bid their true valuations.

Compared to other auction mechanisms, the Dutch Auction was chosen due to several of its unique properties. First, the descending prices encourage bidders to bid quickly after their valuation is reached. Second, the process is easy and simple to implement using standard tools such as an online interface. Only a single bid is required to win an auction and participants are therefore not necessarily aware of any other bids. By having a Dutch Auction online, auctions can be drawn out over longer time periods, preventing scheduling conflicts, utilizing proxy bids in order to reduce the amount of participation time required for each bidder. Finally, the process is transparent to all participants, emphasizing fairness and understanding.

All auctions were conducted separately in the following manner. At the beginning of every auction, the total number of permits to be sold (supply) was announced to the online bidders. The starting price for each auction was estimated to be higher than what bidders were expected to pay. After the auction began, the price was reduced by a constant amount per specified time interval between 9:00am and 9:00pm everyday throughout the duration of the auction. For example, the reserved permits began at a high price of \$1270 and were reduced by \$20 at regular intervals of time throughout the day. At any time during the auction, bidders could accept the current price listed in order to be assured a spot. Bidders could also make

proxy bids by entering the highest price they would be willing to pay (provided that the price was below or equal to the current listed price). In the reserved auctions, bidders could choose their specific parking space, where spots were chosen according to the order in which the bids were received. For all other permits, permit holders would have access to any space within the applicable lot. All ties were broken chronologically by a bid's time stamp. In all cases, each bidder paid the uniform market clearing price. Additionally, because bidders could register while auctions were being conducted, there was no upper bound for the total number of potential bidders.

The primary strength of this dataset is that it represents, to the knowledge of this researcher, the only example of a university that has attempted to sell a large number of parking spaces using Dutch Auctions. Additionally, anonymous bidder identifying numbers, bid timestamps, and three distinct locations varying in value make this dataset particularly well suited for the study.

The primary disadvantage to this dataset is that bidders are not identified as students, faculty, or staff members at Chapman. Another disadvantage is that the data is incomplete. Auctions were held beyond the Fall 2010 period between 2009 and 2011. In addition, the majority of permits at Chapman were not sold using auctions. Instead, only a few hundred of the most desirable reserved spaces and spaces in on-campus lots were selected to be auctioned, due in part to avoid public opposition and to avoid accusations of elitism. Furthermore, the number of bidders for each auction was relatively small due to low awareness and confusion about the auction process. The data are also limited to Chapman, which has a unique set of commuting patterns for faculty, staff, students, and visitors. Despite these disadvantages, early analysis of the data indicates its strength, with supply and demand and bid timing, discussed in

the empirical specification, resembling results found in other auctions-centric papers (Bajari & Hortacsu, 2003). A more comprehensive dataset might include a wider selection of universities, where more students living either on or off campus, contrast urban, suburban, and rural environment settings, and contain key information about how bidders are affiliated with a university. Despite these weaknesses, the data remain strong by clearly demonstrating how individuals respond to auction set prices, indicating allocative efficiency.

B. Auction Summary Statistics

The Chapman dataset consists of 843 observations spread across 29 variables. Variables of importance include location ID, unique ID (to anonymously identify the bidder), bid amount, location ID, bid accepted (a binary variable indicating whether the bid was accepted), bid canceled (indicating whether the bid was canceled), bid timestamp, auction start timestamp, auction end timestamp, minimum bid (reserve price), maximum bid (auction start price), and the amount decreased per time interval (Appendix, Table IV-A). A simple program was written in order to convert auction timestamps into more useful time-based variables such as the number of minutes between the start of an auction and the casting of a bid, and the fraction of the auction surpassed at each bid.

In the Fall of 2010, permits were sold in the following lots: Argyros, Reserved, and Villa Park. Villa Park had the cheapest permits, with a starting bid of \$50; Reserved spaces and Argyros spaces started at \$1270 and \$225, respectively. For the reserved lot, the minimum bid was \$270. For all other lots, there was no minimum bid. For each lot, a different interval was selected to decrease the price every time segment during the auction, ranging from \$1 to \$20. Argyros had the most permits to sell, with 175, whereas reserved represented the least permits to sell, with 67 permits. While Villa Park and Argyros refer to specific lots, permits marked

reserved could be found in a variety of lots. A full list of auction characteristics separated by lot can be found in the table below (Table IV-B). A map of the relevant lots is provided in the appendix (Figure IV-A).

Table IV-B: Permit Auction Characteristics

Lot Name	Starting Bid	Min Bid	Bid SD	ADPI^a	Supply	Demand^b
Villa Park	50	0	25.46	\$1	100	109
Reserved	1270	270	404.85	\$20	67	87
Argyros	225	0	76.33	\$3	175	288

^a ADPI = Amount Decreased Per Interval

^b Total number of non-canceled bids (i.e. bids not retracted before the end of an auction).

C. Demographic Information

The demographic and human resources data accessed through The NCES contains dozens of tables full of useful information about the students, faculty, and staff at Chapman University between 2010 and 2011. Highlights of the dataset most relevant to the study include: demographic information for full-time and part-time undergraduate and graduate students, a headcount of all students, both full-time and part-time, information regarding the number of undergraduate students who live off-campus, average salary information for full-time and part-time faculty and staff, and a headcount for all full-time and part-time staff. Summary statistics for the NCES dataset for Chapman University 2010-2011 are listed in the table below (Table IV-C).

A major strength of this resource is that it is an official government report filed by Chapman University, providing a high level of detail and accuracy. Additionally, the data are from the same year as the parking permits at Chapman, enhancing the accuracy of the model. However, a downside of the data is that there is no information regarding how many faculty,

Table IV-C: Chapman University Population Size (2010-2011)

Affiliation	Full-time ^a	Total ^b
Students	5,621	6,881
On Campus Undergrad	1,329	1,530
Off Campus Undergrad	2,935	3,380
Grad Student	1,357	1,971
Professional Staff	725	1,112
Teaching & Research	370	704
Administrative & Support	355	408
Non Professional Staff	254	272
Technical and Skilled	223	241
Service & Maintenance	31	31

Source: Chapman University, Human Resources Report (2010-2011). U.S. Department of Education. Institute of Education Sciences, National Center for Education Statistics.

^aNote: All values are population head counts

^bNote: "Total" refers to Full-Time + Part-Time

staff, and students regularly drive to campus. This requires an estimate of the number of drivers for each group provided in a later section in order to perform critical analysis.

Another difficulty with the data is that information is reported for both full-time and part-time staff. The decisions to include part-time staff in my analysis is not straightforward, but reflects the fact that part time students and faculty still have a need to purchase parking permits in order to commute to campus. Because students, faculty, and staff can all have full-time or part-time positions, I have included data for both "Full-time and "Total", defined as full-time + part-time, affiliates. For consistency and simplicity, I will discuss "Total" numbers unless otherwise specified.

The definition of faculty and staff also creates challenges. In the tables accessed, a distinction is not drawn between faculty and staff directly; rather, the tables use the categories "Professional Staff" and "Non-Professional Staff". As defined by the dataset, Professional-Staff

refers to all instructors (teachers), researchers, public service people, executives, administrators, managers, and other support and service professionals, whereas Non-Professional Staff refer to all technical and paraprofessionals, clerical and secretarial personnel, skilled craftsman, and service and maintenance staff members. The decision whether to include administrators, executives, and other professionals in my definition of faculty or staff is discussed in a later section.

V. Empirical Specification

At a basic level, I am trying to determine the effect university affiliation has on predicting bid values. However, since only a unique identifier is provided for each bidder, there is no way to confirm what group an individual is associated with. Doing the best I can given my circumstances, I use K-means and K-medians cluster analysis to divide the bids into a specified number of groups and compare the distributions with demographic data in order to determine the goodness of fit. Finally, I run regressions using the new groups as a series of independent binary variables in order to determine if university affiliation can be used to improve bid predictions. This would suggest that a person's affiliation with a university has a sizable effect on their valuation of parking.

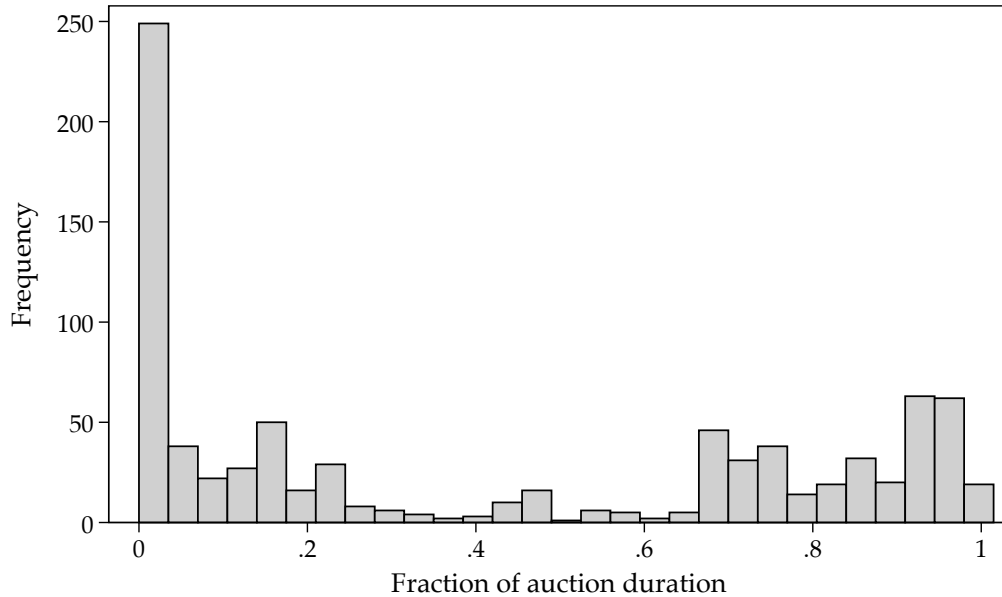
Before examining the evidence to answer this research question, there are some general empirical observations to be discussed. Observations on the timing of the bids are included and supply and demand is calculated in order to visualize the market clearing prices.

A. Bid Timing

When visualizing bid time, a dramatic feature evident is that bidding activity is most frequent at the beginning of each auction. To illustrate this, a histogram showing the frequency

of bid submissions per fraction of auction duration surpassed at the time of the bid, not accounting for repeat bidders who canceled their bids, is provided below (Graph V-A).

Graph V-A: Distribution of Bid Times at Chapman (Fall 2010)

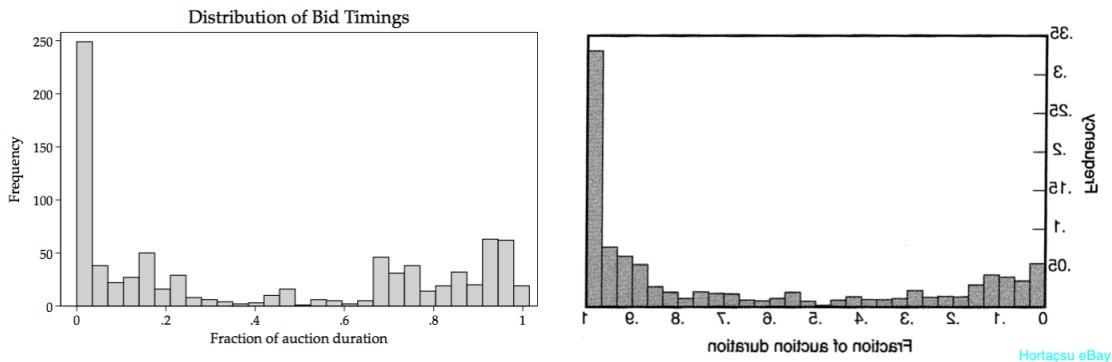


Considering all bids, more than 36-percent were submitted in the first 10-percent of the auction duration (307 out of 843), and more than 27-percent were submitted in the first 3-percent of the auction (236 out of 843). Excluding canceled bids, the results were almost identical, differing only by a fraction of a percent between the corresponding statistics above. More than 36-percent of these bids were submitted in the first 10-percent of the auction duration (173 out of 477), and more than 27-percent were submitted in the first 3-percent of the auction (133 out of 477). Intuitively, winning bids, defined here as accepted, not canceled, and greater than or equal to the market clearing price, also tended to occur earlier. Over 32-percent of winning bids occurred within the first 1-percent of the auction duration (on average, within the first two hours of an eight day auction)

I found my results to have some striking similarities to other results in the literature. In a series of empirical insights presented in a paper on eBay ascending price coin auctions by Bajari

and Hortasçu, a histogram of final bid submission times is presented, indicating, contrary to my results, that bids are most frequent at the end of auctions (2003). This difference can be neatly explained by the fact that the eBay auctions were ascending whereas the parking permit auctions at Chapman were descending in price, resulting in bidder frequency being the highest at the start of an auction. Interestingly, despite the differences between parking permits and treasury bonds, and the relatively small size and low participation characteristic of the Chapman auctions, the graphs are practically mirror images of each other, neatly affirming the auction mechanism theory discussed in previous sections. To illustrate these similarities, I have attached a comparison of my graph and a horizontally flipped, mirrored version of the relevant graph from the Bajari and Hortasçu paper below (Figure V-A).

Figure V-A: Comparison Between Distributions of Bid Timings



Source: Auction data from Chapman 2010 (left) and Figure 1 from Bajari, P., & Hortacsu, A. (2003). The winner's curse, reserve prices, and endogenous entry: Empirical insights from eBay auctions. *RAND Journal of Economics*, 329-355. (right).

Note: The graph on left is a copy the histogram of final bid submission times from my study for Chapman permit auctions in Fall 2010, excluding canceled bids. The graph on the right is a horizontally flipped, mirrored copy of a histogram of final bid submissions from a Bajari and Hortasçu paper on eBay coin auctions in 2003.

B. Supply and Demand

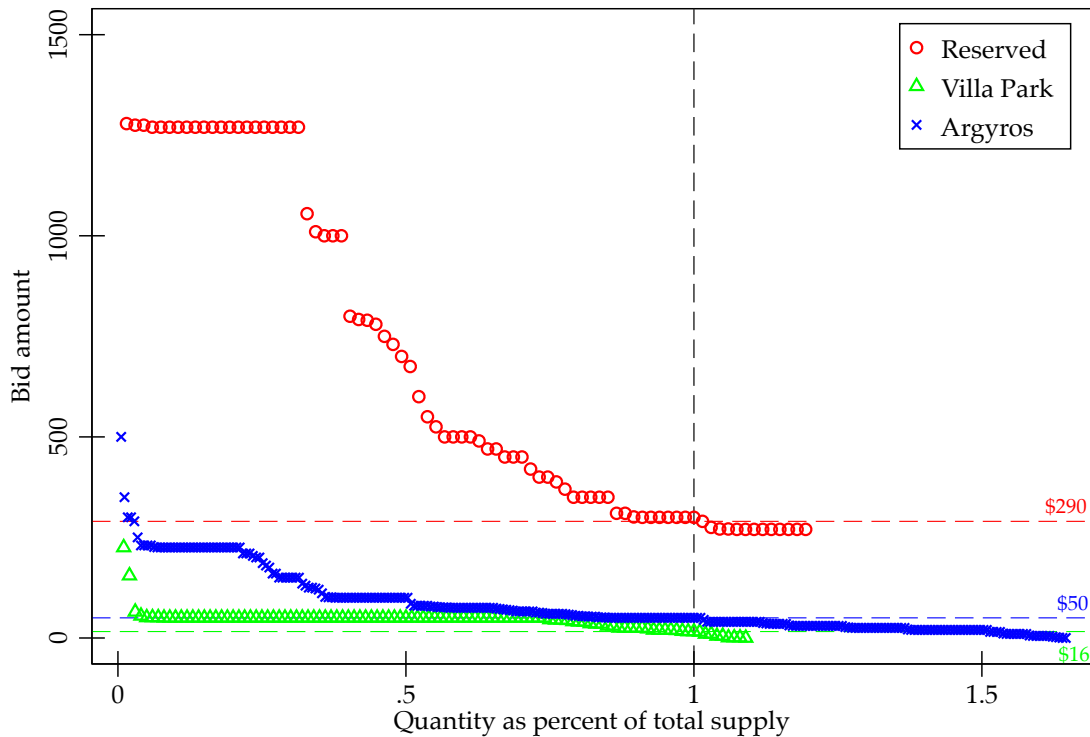
Analyzing supply and demand provides crucial insights on the effectiveness and efficiency of an auction. Supply and demand were analyzed for each of the parking locations present in the data set for Fall 2010, representing the Villa Park Orchard, Reserve, and Argyros

lots at Chapman University. I found the market clearing prices for the Villa Park Orchard, Reserved, and Argyros lots to be \$16, \$290, and \$50, respectively. Villa Park Orchard was found to have the least variance in bid value while the reserved lot had the highest variance (Table IV-B). Canceled bids were not considered when analyzing supply and demand. It is important to note, as mentioned previously, that because the goods being sold are private and the goods are sold at the market clearing price, the bids are essentially equivalent to the true valuations of the bidders.

To calculate supply and demand, the data was first separated by lot. All canceled bids were removed from the dataset. Next, bids were ranked from largest to smallest in their respective auctions. Bids were then graphed on a scatter plot with bid value on the vertical axis and percent capacity on the y-axis. The bids that intersect the vertical line at the 100-percent mark on the horizontal axis (labeled "1" on the corresponding graph) represent the market clearing prices for each auction. Diagrams of supply and demand for the Villa Park Orchard, Reserved, and Argyros lots can be found in the graph below (Graph V-B).

The market clearing prices for the Reserved, Argyros, and Villa Park lots were \$290, \$50, and \$16, respectively. The supply, which is inelastic, is represented by the dashed vertical line, intersecting the market clearing price for each auction (at $x = 1$). The supply for the Reserved, Argyros, and Villa Park lots were 67, 175, and 100, respectively. These prices reflect the appeal of each lot. Buyers of reserved spaces were able to choose specific spaces from a variety of lots around campus. Bidders were incentivized to bid earlier in this auction because winners were allowed to select specific spaces in the order in which their bids were received. The bidder who cast the first winning bid selects the best parking space. The other two lots were likely less

Graph V-B: Supply & Demand for Chapman Lots in Fall 2010



convenient to the average bidder. The Argyros lot sat* adjacent to Wilson Field† (home of Chapman’s football program) and the Argyros student center, remaining a convenient but less desirable location compared to the reserved spaces. The Villa Park Orchard lot was likely the least convenient lot of the three to the average bidder, residing across the street from the Dodge College of Film and Media Arts.

Interestingly, in accordance with basic economic theory, the demand for the Reserved lot is more inelastic as it lacks substitutes, serving as the only lot where bidders can pick their exact parking spaces. Demand for the Villa Park and Argyros lots were more elastic, with demand more sensitive to price changes.

* The Argyros lot has since been demolished to make way for the Schmid College of Science Building.

† Chapman’s prime parking garage is located under Wilson Field. According to parking officials at Chapman, nearly 66-percent of reserved space winners chose a parking space in this garage, suggesting that the Argyros lot was generally a more desirable location than the Villa Orchard Park lot.

C. Clustering

While information concerning bid-time, minimum bid, maximum bid, location, number of bidders, and other useful variables are present in the Chapman auction dataset, there are no data variables available that reveal a bidder's affiliation with the university (i.e. whether a bidder is a student, faculty, or staff member). Using clustering techniques, I seek motivating evidence for the existence of three unique groups of bidders across auctions in order to better predict bid values. Using the results from several different clustering techniques, I compare the groups generated with demographic information describing Chapman's student, faculty, and staff populations in 2010 in order to determine how well these groupings fit my data. Finally, I run a regression to determine if bid values are better predicted by these groupings. Dependent upon the accuracy of these grouping, the analysis implies the extent to which university affiliation affects bid value, controlling for other factors.

Many examples of econometricians using clustering techniques to study auctions can be found in the relevant literature (Drachen, Riley, Baskin, & Klabjan, 2014; Zhang, Jank, & Shmueli, 2010). In many cases, clustering techniques have been used to classify entire auctions into discrete clusters in order to help forecast prices and determine bidding strategies (Kaur, Goyal, & Lu, 2011). In contrast to these particular studies, I use clustering techniques to identify groups of bidders instead of groups of auctions.

A major difficulty in using clustering techniques is specifying the correct number of clusters. In many studies, the number of groupings is unknown, making it difficult to obtain good results. Finding the right number of clusters is imprecise and the fact that increasing the number of clusters reduces the error observed creates difficulties. Because I aim to identify the presence of three unique clusters, I circumvent this issue. However, because there is a possibility

that the three groupings do not correspond to university affiliation, or that university affiliation is better broken up into a greater number of groups, the groupings should be rejected if they do not fit the demographic information relevant to Chapman University's parking population.

1. K-means Clustering.

K-means clustering (MacQueen, 1967) is a widely used clustering technique that aims to identify a user-specified number of clusters (K) which are each represented by centroids. There are a wide variety of techniques for identifying centroids, but the simplest and most widely used methods use the mean, median, or a group of points as specified by a relevant algorithm (Tan, Steinbach, & Kumar, 2006). Clusters are created by partitioning data objects in a continuous n -dimensional space.

Tan et al. outline the algorithm for K-means clustering in four steps (2006). First, K centroids are chosen randomly (unless otherwise specified), with K representing the number of clusters desired by the statistician. Second, each observation is assigned to the closest centroid, where the collection of observations corresponding to each centroid is a cluster. Third, centroids are recalculated to reflect the observations attached. Fourth, steps two and three are repeated until centroids minimize the objective function

$$J = \sum_{j=1}^k \sum_{i=1}^n \left\| x_i^j - c_j \right\|^2 . \quad (1)$$

In this function, $\|x_i^j - c_j\|^2$ refers to the distance between a data point x_i^j and the relevant cluster c_j . In this way, I use K-means clustering to identify different types of bidders with respect to their affiliation with Chapman University based on bid amount for all non-cancelled bids. In addition to K-means clustering, I employ K-medians clustering techniques for the same purpose. The

commonly used K-medians test closely resembles the K-means test, but uses a real median instead of a randomly selected mean.

2. K-Selection and Chapman Demographics.

I examined students, faculty, and staff in my clustering analysis, representing a K value of three ($K=3$). This was a straightforward decision for multiple reasons. First, when looking at a parking map (Figure IV-A), Chapman lists parking for four university affiliations: students, faculty, staff, and visitors. Because visitors have no reason to purchase an annual or semester-long parking pass, I am not considering visitors in my analysis. Going deeper, it makes sense to divide Chapman's parking population into these groups because the unique characteristics of each group translate into different parking needs. Students living off-campus commute daily to class at irregular times depending on their own schedules. Their willingness to pay (as noted in the literature review) can often be high due to the fact that their parents can subsidize the cost of a parking permit, translating into preferences that do not necessarily reflect their incomes. Faculty also have irregular schedules that vary from day to day. Unlike the students, the willingness to pay of this group may be more directly linked to what they can afford. Finally, staff members generally work regular schedules. I hypothesize that these differences will translate into systematically different bidding behavior.

It is possible that being a part-time affiliate (opposed to a full-time affiliate) may have an effect on bidding behavior. If a student is part-time, it is possible that they might be less likely to bid on a parking permit due to the fact that they do not commute to campus everyday. Likewise, part-time faculty and staff might not want to pay for a space that they do not regularly use.

Before performing the clustering analysis, it is necessary to develop an estimate of the true number of parkers belonging to each university affiliation group at Chapman. These population estimates of parkers, derived from the university demographic information presented previously (Table IV-C), are used to crosscheck the realism of the clusters generated in the K-means and K-medians analysis performed in later parts of this paper. Because of a lack of access to the information regarding the number of parkers at Chapman by university affiliation, I made several key assumptions for my estimates. First, to calculate the number of students parking on campus, I did not include on-campus undergrads in my tabulation due to the fact that the relevant lots were open overnight, suggesting that the permits were intended for daytime use only. For this reason, I only considered graduate students and off-campus undergrads in my driving student category. Using information provided in the Chapman demographics dataset, I assumed that 69-percent of undergraduates lived off campus and that 85-percent of all undergraduate students had cars.

However, information about the number of driving graduate students, professional faculty, and non-professional faculty is less certain. In an American Community Survey of 5-Year Estimates, The U.S. Census Bureau provides approximations of the percent of commuters who drove to work regularly in different parts of the United States between 2006-2010 (2010). According to this resource, in Orange County, California*, nearly 89-percent of all workers sixteen years-old and over commuted to work by car, truck, or van, with almost 78-percent of those commuters indicating that they drove alone. In both cases, these statistics for Orange County, CA were ten percentage points greater than the numbers reported for Los Angeles, a city known for its high driving participation. For this reason, I estimate the number of parkers

* Redundantly, Chapman University is located in the city of Orange, California, which resides within Orange County, California.

for each of the remaining university affiliate groups by multiplying the appropriate numbers derived from the demographic information for each category by 90-percent, in accordance with the information found in the U.S. Census for Orange County commuters. Additional statistics for alternative modes of transportation taken to work in 2010 for Orange Country, California and Los Angeles, California can be found in the appendix (Table V-A).

An estimated 4,647 students have cars at Chapman. Students consist of on-campus undergraduates, off-campus undergraduates, and graduate students. Due the highly suburban characteristics of Orange, CA (where Chapman is located), and the number of people driving to work estimated by the U.S. Census, it is reasonable to assume that almost all graduate students living off-campus also own cars. While I have presented information for each category in the table below (Table V-B), I will refer to total students (both part time and full-time) unless otherwise noted.

The number of faculty and staff estimated to drive to work is 634 and 581, respectively (Table V-B). Defining faculty is not straightforward. While most definitions of faculty include those who teach or perform research, deciding whether or not to include administration and support in the category remains a matter of uncertainty. On one hand, administration and support personnel are highly educated and work closely with teachers and researchers. On the other hand, administration and support generally work a regular and fixed schedule, whereas teachers and researchers have schedules that very depending on when their classes are held. Furthermore, while the literature suggests income does not have a significant effect on affiliates' willingness to pay for permits, income does determine what individuals can afford (Sultana, 2015). For this reason, I have included two categories to describe faculty and staff. In category (a), faculty includes teachers & researchers and administration & support, and staff includes all

Table V-B: Chapman University Driving Population Estimate (2010)

Affiliation ^a	Full-time ^b	Total ^c
Undergrads with cars ^d	2,495	2,873
Grads students with cars ^e	1,221	1,774
(a) Faculty with cars (teaching & research + administration support)	653	1,001
(a) Staff with cars (non-professional staff)	198	214
(b) Faculty with cars (teaching & research)	333	634
(b) Staff with cars (administration & support + non-professional staff)	517	581

Source: Chapman University Human Resources Report (2010-11). U.S. Department of Education. Institute of Education Sciences, National Center for Education Statistics.

^aNote: Defining faculty and staff is tricky. You can classify faculty as teachers and administrators (grouping a) or as teaching only (grouping b). I compare clustering techniques with both to find the best fit.

^bNote: All values are rounded estimations of population head counts

^cNote: "Total" refers to Full Time + Part Time

^dNote: University statistics suggest 85-percent of students have cars in 2014. Not including 31-percent of students who live on campus since permits are not residential.

^eNote: Based on census data, 90-percent of the remaining affiliates were assumed to drive.

non-professional staff. In category (b), faculty includes teachers & researchers only, and staff includes both administration & support and non-professional staff. While all categories are presented in the table above, I will refer to faculty and staff using category (b) unless otherwise specified (Table V-B).

Using this demographic and population information as a guide, the three groups representing all university affiliates can be justified. Additionally, it is clear that students are the largest of the three groups of parkers on campus, representing over 80-percent of the estimated total number of parkers. Faculty and staff represent significantly smaller portions of the total number of parkers each.

3. Clustering Results.

I conducted two separate cluster analyses to determine two sets of three groupings ($K=3$) using all data from the three auctions available. The first cluster analysis was performed using the K-means method, whereas the second cluster analysis used the K-medians method. With each cluster analysis, a new variable was generated, classifying each bid observation as a member of one of three groups. In order to be used in a regression, each new variable generated by the cluster analysis was split into three dummy variables. In this analysis, I only considered non-cancelled bids. The populations of each category for the two cluster analysis can be found in the accompanying table (Table V-C).

Reviewing the results from the mean cluster analysis, the data were divided into groups representing 74-percent, 20-percent, and 7-percent of the total data points. Reviewing the results from the median analysis, the data were divided into groups representing 50-percent, 27-percent, and 23-percent of the total data points. Looking at headcount by lot, MeanGroup2

Table V-C: Cluster Analysis Summary

K-mean	Reserved	Villa	Argyros	All Lots	% Share
MeanGroup1	0	108	243	351	73.58%
MeanGroup2	48	1	45	94	19.71%
MeanGroup3	32	0	0	32	6.71%
Total	80	109	288	477	100%
K-medians	Reserved	Villa	Argyros	All Lots	% All Lots
MedianGroup1	0	83	157	240	50.31%
MedianGroup2	80	1	46	127	26.62%
MedianGroup3	0	25	85	110	23.06%
Total	80	109	288	477	100%

Note: Numbers reflect the number of observations put into each category.

preferred the less expensive permits in the reserved sections along with permits in the Argyros lot, MeanGroup1 purchased the majority of the permits in the Argyros and Villa lots, and MeanGroup3 purchased the most expensive permits in the Reserved lots. Slightly different results were observed in the K-medians analysis.

In order to determine if the categories presented are a good fit for the data, I compare these results with the table below (Table V-D) containing demographic information about the estimated number of drivers for each group of faculty, students, and staff at Chapman University. In Table V-D, I list four possible groupings of the demographic information, based on different definitions for Faculty and Staff, considering both Full-Time and Total-Time affiliates. Looking at the data, it is likely that students should correspond with MeanGroup1 and MedianGroup1 due to their large size, but it is initially unclear whether the remaining

Table V-D: Chapman University Drivers Est. by Affiliation (2010)

Affiliation	Full-time	(weight)	Total ^a	(weight)
	Group 1:		Group 2	
Students ^b	3716	81%	4547	79%
(a) Faculty ^c	653	14%	1001	22%
(a) Staff ^d	229	4%	245	4%
	Group 3		Group 4	
Students ^b	3716	81%	4647	79%
(b) Faculty ^e	333	7%	634	11%
(b) Staff ^f	520	11%	584	10%

Source: Chapman University Human Resources Report (2010-11). U.S. Department of Education. Institute of Education Sciences, National Center for Education Statistics.

^a Note: "Total" refers to Full Time + Part Time

^b Students = All Students - on-campus undergrads

^c (a) Faculty = Teaching & research + administration & support

^d (a) Staff = Non-professional staff - maintenance

^e (b) Faculty = Teaching & research only

^f (b) Staff = Administration & support + non-professional staff - maintenance

groups should be classified as faculty and staff. Based on the distribution of the bids, I assume that MeanGroup1 and MedianGroup1 corresponds with students, MeanGroup2 and MedianGroup2 correspond with faculty, and MeanGroup3 and MedianGroup3 corresponds with staff. The model suggest that faculty is better defined as teaching and research personnel only due to the fact that the relative weights align better in those situations. While these results are far from conclusive, they provide motivation that these clusters are good approximations of university affiliation, and therefore have some effect on predicting bid value.

Since these groupings are partially subjective, I conducted sixteen chi-squared goodness of fit tests to determine the plausibility of each combination of faculty and staff definition and median and mean grouping (Appendix, Table V-E). Comparing Full-time Affiliates, where the definition of staff includes university administrators, with the median groupings, a chi-squared goodness of fit test suggested that I was unable to determine with statistical significance that the groups were not a good fit ($\chi^2 = 74.725$, $p < .001$). Similar results were found to be significant for all but two of the sixteen tests at the .05 level, representing a failure to reject the null hypothesis. The only two groupings that could be eliminated by the chi-squared testing compared the mean groupings with Group1 and Group2, where faculty was equated with MeanGroup2. In other words, I can conclude that neither Full Time or Total Time affiliates are a good match for the groups generated by the K-means analysis when faculty is equated to MeanGroup2 and staff is defined to be non-inclusive of the university administration. It is important to remember that the chi-squared tests only suggest that the estimated groupings and the generated groupings are statistically possible representations of each other, and not necessarily a perfect fit. Additionally, differences in chi-squared values do not suggest that one test is a better fit than another.

D. Regression Analysis

In this analysis, a log-linear model is used in order to illustrate the impact of independent variables on predictions as percentages. The dependent variable in this study is the natural log of the bid amount. The independent variables are lot location (represented by three dummy variables for each with one lot omitted), fraction of auction duration (the number of minutes since the start of the auction at the time the bid was made divided by the total number of minutes in the auction), and bidder affiliation (represented by three dummy variables for each value with one omitted).

The three regressions can be summarized as:

$$\ln(\text{BidValue}_i) = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_7 X_i + u_i \quad (1)$$

$$\ln(\text{BidValue}_i) = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_3 D_{3i} + \beta_4 D_{4i} + \beta_7 X_i + u_i \quad (2)$$

$$\ln(\text{BidValue}_i) = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_5 D_{5i} + \beta_6 D_{6i} + \beta_7 X_i + u_i \quad (3)$$

where D_{1i} and D_{2i} are dummy variables for the Reserved and Villa Orchard parking lots, respectively, D_{3i} and D_{4i} are dummy variables for Group 2 and Group 3 in the K-means cluster analysis, respectively, and D_{5i} and D_{6i} are dummy variables for Group 2 and Group 3 in the K-medians cluster analysis, respectively. Furthermore, X_i refers to a vector representing the fraction of the total duration of the auction surpassed at the time of the bid. The response variable is the natural log of the bid amount. The sample size in all regressions was 477 ($n=477$) due to the fact that cancelled bids were not considered in any of the regressions. Results for Regressions (1), (2), and (3) can be found in the table below (Table V-F). An explanation of how to convert these results into percentage impacts for both dummy and continuous variables can be found in the Appendix (Figure V-B).

Table V-F: Regression Analysis

ln(Bidamount)	Regression (1)		Regression (2)		Regression (3)	
	Coef.	SE	Coef.	SE	Coef.	SE
Reserved	2.292***	(0.109)	0.507***	(0.149)	0.922***	(0.095)
Villa	-0.493***	(0.098)	-0.186*	(0.083)	-0.325***	(0.060)
MeanGroup2	-	-	1.640*	(0.118)	-	-
MeanGroup3	-	-	2.723***	(0.204)	-	-
MedianGroup2	-	-	-	-	1.207***	(0.086)
MedianGroup3	-	-	-	-	-1.356***	(0.060)
FracOfAucDur	-0.590***	(0.101)	-0.170*	(0.087)	-0.088	(0.063)
_cons	4.295***	(0.07)	5.473***	(0.105)	4.251***	(0.050)
R-squared	0.56		0.70		0.84	

*** Significant at the 0.1-percent level, ** significant at the 1-percent level, * significant at the 6-percent level.

The most striking result found in the table above is the improvement in R-squared between Regression (3) and Regression (1), representing an increase of 27 percentage points, from 0.57 to 0.84. This suggests that the K-medians cluster grouping technique had a large impact on helping predict bid values across all auctions. However, the difference between R-squared in Regression (2) and Regression (1) is 14 percentage points, from 0.56 to 0.70, suggesting that the K-means clustering technique was slightly less effective in helping predict bid values. Operating under the assumption that these clusters are accurate representations of university affiliation for bidders, the regression indicates that determining whether a bidder is a staff member, faculty member, or student is crucial for predicting bid values. However, there is no strong evidence proving these cluster are completely accurate representations of affiliation, meaning that the high R-squared observed could be capturing some other systematic three-way

division in the data. Nevertheless, at the very least, the clustering is providing a realistic simulation of a potential mapping of university affiliation for the bids provided. While the magnitude of each affiliation might vary from study to study depending on circumstances such as the university selected, it remains clear that university affiliation is a key metric for predicting bid values.

The major finding from these results is that university affiliation has a larger impact on predicting bid amount than all other variables including lot location and auction duration. By comparing the variables across Regression (2) and Regression (3), it is evident that the variables Reserved and Villa have smaller coefficients than what was observed in MeanGroup2 and MeanGroup3 in Regression (2) and in MedianGroup2 and MedianGroup3 in Regression (3). In Regressions (2) and (3), switching from Argyros to Reserved represented a rounded 66-percent and 151-percent increase in predicted bid amount, respectively.* Similarly, in Regressions (2) and (3), switching between the Argyros to Villa lots represented a rounded 17-percent and 28-percent decrease, respectively. Across the same regressions, bidder affiliation had a greater percentage impact in predicted bid amount, with a switch between MeanGroup1 and MeanGroup2 representing a 415-percent increase in Regression (2) and a switch between MedianGroup1 and MedianGroup2 a 234-percent increase in Regression (3). Between MeanGroup1 and MeanGroup3, a 1423-percent increase was observed Regression (2), and between MedianGroup1 and MedianGroup3, a 288-percent decrease was observed in Regression (3). Predictably, the impact of lot location decreases as university affiliation is considered. These results signify the importance of considering university affiliation when

* An explanation of how to convert results presented in Table V-F into percentage impacts for both dummy and continuous variables can be found in the Appendix (Figure V-B).

designing an auction for university parking permits due to the fact that these differences have the most significant impact on bid amount than any other factor.

Reinterpreting the same results after identifying the median groups with the categories suggested by the demographic data provides meaningful insight. Using the K-medians results found in Regression (3), Staff and faculty were predicted to bid 74-percent less and 234-percent more than students, respectively. However, in Regression (2), staff were found to pay more than students, complicating the results. However, due to the higher R-squared value, the more promising chi-squared goodness of fit results (Appendix, Table V-E), the more realistic distribution of the K-median groupings, and properties of the median giving less weight to outliers, I prefer the results from Regression (3). However, the main finding of this study is that university affiliation had the largest impact on the dependent variable. Regardless of whether the coefficient for a particular group is negative or positive, which is likely to vary by university depending on the demographics, this has important implications for any parking administrator.

The mechanism of a reverse auction, which mandates that the bid amount be reduced by a constant value per unit of time, vindicates Fraction of Auction Duration as a valuable predictive variable. However, its lack of statistical significance in the regressions above suggests the necessity of a more nuanced approach. In contrast to assumptions made in the model, there is no reason to believe that Fraction of Auction Duration has consequences of equal magnitude across auctions. The permits for the Argyros lot were sold in a slightly shorter auction that took place after the other two were conducted simultaneously. In addition, the Reserved lot provided a greater incentive for early bids due to the fact that winners would chose reserved parking spaces in the order their bids were received. One possible solution to this problem is to generate a variable that is the product of the amount decreased per interval and the Fraction of Auction

Duration. However, after trying three different solutions, I was unable to increase the significance of the variables relating to Fraction of Auction Duration, leading me to prefer the regression results already presented. Results from alternative regressions (Regressions 4-9) are located in the appendix (Table V-G).

While the regression results for the K-means test were significant and offered impressive improvements in the model's predictive ability, the results are less meaningful in answering the research question until the accuracy of the clusters is determined. While the clusters do not match any of the demographic data perfectly by their weight, an argument can be made for similarities between the demographic data and the cluster distribution. In future studies, it is essential to measure university affiliation as an important variable in determining bid value.

VI. Conclusion

In this study, I found that university affiliation had a larger impact on bid amount than any other considered predictive variable. According to one model presented, holding all other variables constant, staff and faculty were estimated to bid 74-percent less and 234-percent more than students, respectively. In different cases, staff were found to pay more or less than students, without clear results. On average, student bids were more closely clustered together whereas faculty bids were more spread apart. The affiliation groups explain much of the variation in bid values observed, suggesting the high importance university affiliation represents when conducting auctions of permits.

Demand-based parking has the potential to alleviate congestion, giving parking priority to those who value it the most. However, for a system to be optimal, it needs to reward those who value it the most, not just those who can afford it. The main finding of this project, that university affiliation definitively helps predict and bid values, suggests that an auction planner

should take university affiliation into careful consideration when designing future experiments. At Chapman, many students, faculty, and staff voiced their opinions against the use of auctions, claiming that the auctions were elitist and favored certain groups systematically based on income, facts that were not backed up by economic research examined in the literature review. While a uniform-price reverse auction may allocate permits more efficiently, the existence of a systematic bias across university affiliation is not ideal for a university planner. To combat this, policy makers might consider creating lot specific auctions for each affiliate group as to prevent this bias in the future. These results can be applied to projects outside of the university. When planning on auctioning parking in cities, planners may consider selling permits to individuals in different auctions differentiated by affiliation groups defined by their distinct commuting needs and patterns.

Despite this, using a Dutch Auction, there is a high potential to better capture consumer valuation of parking spaces. The relevant auction theory suggests that bidders in these parking auctions were incentivized to bid their true valuations, a fact on which the value of this study's empirical results hinges. Further avenues for study include exploring the role auctions play in encouraging students, faculty, and staff to take other forms of transportation, substituting away from cars. In addition to examining mode shifting behavior, researchers could explore the effects of implementing demand-based parking on an hourly basis. Pricing parking by demand on an hourly basis has the potential to fix congestion problems to an even greater degree. However, there are many challenges to this; commuters may be hesitant about participating in a daily auction. Nevertheless, it is reasonable to assume bidders could purchase annual permits for specific time slots (e.g. Monday-Friday 10:00-11:00am). If the price of parking at 10:00am became more expensive than 4:00pm, more professors might schedule their classes later in the

day. In conclusion, parking is an under-researched area of economics, with a lot of potential for innovative research. I encourage the reader to think about the benefits of demand-based parking and consider its implementation to alleviate parking congestion in a university near you. However, if the reader is encouraged to perform such a study, be certain to keep track of bidders' university affiliation in order to push this area of research even further.

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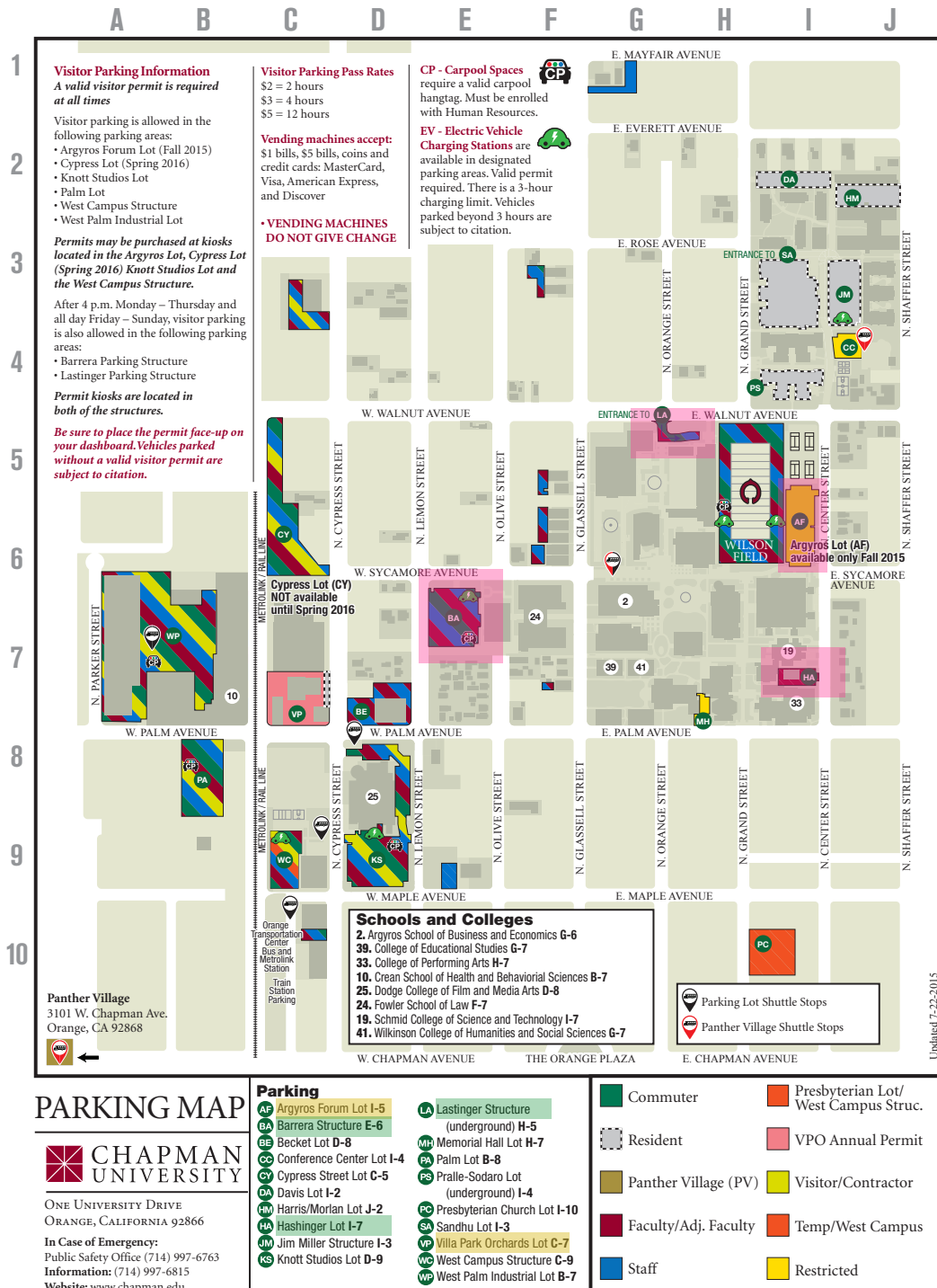
VIII. Appendix

Figure I-A: UNC 2015-2016 Employee Parking Permit Fees

2015 - 2016 Employee Permit Fees					
Permit Type		Salary Range	Annual Price	Weekly Price	Daily Price
All Gated & Reserved Spaces (ALG/RS)	X	<\$25,000	\$1,065.00	\$20.48	\$5.50
	A	\$25,000 - <\$50,000	\$1,172.00	\$22.54	
	B	\$50,000-\$100,000	\$1,479.00	\$28.44	
	C	>\$100,000	\$2,286.00	\$43.96	
All Gated Spaces (ALG)	X	<\$25,000	\$799.00	\$15.37	\$4.50
	A	\$25,000 - <\$50,000	\$880.00	\$16.92	
	B	\$50,000-\$100,000	\$1,109.00	\$21.33	
	C	>\$100,000	\$1,714.00	\$32.96	
Reserved Space	X	<\$25,000	\$717.00	\$13.79	\$4.25
	A	\$25,000 - <\$50,000	\$792.00	\$15.23	
	B	\$50,000-\$100,000	\$999.00	\$19.21	
	C	>\$100,000	\$1,543.00	\$29.67	
Gated Space	X	<\$25,000	\$579.00	\$11.13	\$4.00
	A	\$25,000 - <\$50,000	\$639.00	\$12.29	
	B	\$50,000-\$100,000	\$807.00	\$15.52	
	C	>\$100,000	\$1,246.00	\$23.96	
Non-Gated Space	X	<\$25,000	\$440.00	\$8.46	\$3.50
	A	\$25,000 - <\$50,000	\$485.00	\$9.33	
	B	\$50,000-\$100,000	\$610.00	\$11.73	
	C	>\$100,000	\$943.00	\$18.13	
AM, PM, NR, SR, PDV	X	<\$25,000	\$332.00	\$6.38	\$2.75
	A	\$25,000 - <\$50,000	\$363.00	\$6.98	
	B	\$50,000-\$100,000	\$459.00	\$8.83	
	C	>\$100,000	\$709.00	\$13.63	
NPH			\$98.62	\$2.00	
PM-ALG			\$331.00		
Scooter / Moped			\$25.00		
Motorcycle Permit (MC1)	X	<\$25,000	\$185.00		
	A	\$25,000 - <\$50,000	\$202.00		
	B	\$50,000-\$100,000	\$255.00		
	C	>\$100,000	\$394.00		
Motorcycle Permit for on-campus permit holders (MC2)	X	<\$25,000	\$42.00		
	A	\$25,000 - <\$50,000	\$47.00		
	B	\$50,000-\$100,000	\$57.00		
	C	>\$100,000	\$88.00		
Park & Ride Permit	X	<\$25,000	\$227.00	\$6.00	\$2.00
	A	\$25,000 - <\$50,000	\$250.00	\$6.00	
	B	\$50,000-\$100,000	\$300.00	\$6.00	
	C	>\$100,000	\$390.00	\$6.00	

Source: University of North Carolina Website, Parking Information. <http://move.unc.edu/files/2015/07/2015-16-Employee-Permit-Fees.pdf>.

Figure IV-A: Chapman Campus Parking Map



Source: Chapman Website, Parking Information

Table IV-A: Description of Dataset Variables

Variable	Type	Explanation/Notes
id	int	Unique Id
locationid	byte	Permit lot location
timestamp	double	Time stamp for bid
bidamount	int	Bid amount
accepted	str4	1 if the bid was accepted
acceptedtimestamp	str18	Time the bid was accepted
cancelled	str4	1 if the bid cancelled
cancelledtimestamp	str18	Time bid was cancelled
id2	byte	<i>(discarded)</i>
name	str18	Location Name
description	str58	Permit description details
groupname	str8	Semester+Year
grouporder	byte	<i>(discarded)</i>
starttime	double	Time auction associated with bid started
endtime	double	Time auction associated with bid ended
clockstarttime	double	<i>(discarded)</i>
startcountdowntime	double	<i>(discarded)</i>
stopcountdowntime	double	<i>(discarded)</i>
timeintervalseconds	int	Interval of time for regular price decrease auction associated with bid
startingbid	int	Starting bid for auction associated with bid
minimumbid	int	Lowest bid to be accepted for auction associated with bid
amountDecreasedPerInterval	byte	Amount decreased per interval
totalavailablelocations	byte	Total number of parking spaces available in auction
totalavailablepermits	int	Total number of permits being sold in auction
inaddition	byte	<i>(discarded)</i>
auctioncompletedtimestamp	double	<i>(discarded)</i>
finalprice	int	Market clearing price
lastupdateime	str4	<i>(discarded)</i>
UserID	long	Unique anonymous identifier for bidder

Source: Dr. Porter, Chapman University

Table V-A: Work Transportation Mode Stats

Means of Transportation to Work	Orange County	Los Angeles
Car, truck or van	88.5%	78.1%
Drove Alone	77.8%	67.3%
Carpooled	10.7%	10.8%
Public Transport	3%	11%
Other	8.5%	10.8%

Source: U.S. Census Bureau; American Community Survey, 2006-2010 American Community Survey 5-Year Estimates, Table S0801 Commuting Characteristics By Sex.
Notes: Data for workers sixteen years-old and over.

Table V-E Chi-Squared Goodness of Fit Results

Test Configuration ^a	χ^2 -value	P-value	Sig. at .05
MeanGroup (Config 1 ^b) vs. Group 1	5.588	0.061	No
MeanGroup (Config 2) vs. Group 1	20.896	< 0.001	Yes
MeanGroup (Config 1) vs. Group 2	2.531	0.282	No
MeanGroup (Config 2) vs. Group 2	30.784	< 0.001	Yes
MeanGroup (Config 1) vs. Group 3	13.83	< 0.001	Yes
MeanGroup (Config 2) vs. Group 3	7.707	0.021	Yes
MeanGroup (Config 1) vs. Group 4	7.002	0.030	Yes
MeanGroup (Config 2) vs. Group 4	8.571	0.014	Yes
MedianGroup (Config 1) vs. Group 1	86.231	0.001	Yes
MedianGroup (Config 2) vs. Group 1	90.429	< 0.001	Yes
MedianGroup (Config 1) vs. Group 2	72.912	< 0.001	Yes
MedianGroup (Config 2) vs. Group 2	80.659	< 0.001	Yes
MedianGroup (Config 1) vs. Group 3	86.696	< 0.001	Yes
MedianGroup (Config 2) vs. Group 3	85.017	< 0.001	Yes
MedianGroup (Config 1) vs. Group 4	74.725	< 0.001	Yes
MedianGroup (Config 2) vs. Group 4	75.155	< 0.001	Yes

Warning: No meaningful conclusions can be drawn by comparing chi-squared values between tests. Chi-squared values only provide information on whether or not the null hypothesis is rejected.

^a Note: Observed vs. Expected. Values come from Table V-C and Table V-D representing group proportions from the clustering analysis and estimates from the Chapman demographic information, respectively.

^b Note: Config 1 compares MeanGroupII (or MedianGroupII) with faculty and MeanGroupIII (or MedianGroupIII) with staff. Config 2 is the reverse.

Figure V-B: Interpreting Log-Linear Regressions

I use the log-linear model in this analysis in order to show the percentage relationship different variables have on bid amount. For a continuous variable in a log-linear regression, a change in X by one unit is associated with a $(\text{coefficient} * 100)$ percent change in Y . However, this rule changes for dummy variables. If a dummy switches from 0 to 1, the percent impact of the dummy on Y is $100[\exp(\text{coefficient}) - 1]$. If the dummy switches from 1 to 0, the percent impact of the dummy on Y is $100[\exp(-\text{coef.}) - 1]$.

Table V-G: Alternative Regression Analysis

In(Bidamount)	Regression (4)		Regression (5)		Regression (6)		Regression (7)		Regression (8)		Regression (9)	
	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P
reserved	0.549	0.00	0.549	0.00	0.546	0.00	1.109	0.00	1.109	0.00	1.151	0.00
villa	-0.164	0.05	-0.164	0.05	0.041	0.73	-0.343	0.00	-0.343	0.00	-0.290	0.00
MeanGroup2	1.696	0.00	1.696	0.00	1.708	0.00	-	-	-	-	-	-
MeanGroup3	2.768	0.00	2.768	0.00	2.785	0.00	-	-	-	-	-	-
MedianGroup2	-	-	-	-	-	-	1.209	0.00	1.209	0.00	1.256	0.00
Median Group3	-	-	-	-	-	-	-1.362	0.00	-1.362	0.00	-1.367	0.00
Intr*FracOfAuc	-0.011	0.29	-	-	-	-	-0.027	0.00	-	-	-	-
ln(Intr*FracOfAuc)	-	-	-0.011	0.29	-	-	-	-	-0.027	0.00	-	-
FracOfAucDur	-	-	-	-	0.005	0.97	-	-	-	-	0.042	0.61
F*Reserved	-	-	-	-	-0.196	0.41	-	-	-	-	-0.638	0.00
F*villa	-	-	-	-	-0.570	0.01	-	-	-	-	-0.027	0.86
_cons	3.757	0.00	3.757	0.00	3.738	0.00	4.249	0.00	4.249	0.00	4.183	0.00
R-squared	0.70		0.70		0.70		0.85		0.85		0.84	