A New Method for the Direct Measurement of Parking Incentive Response Curve

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ABSTRACT

Knowing parking price response curve allows one to set the price right. This response curve is often estimated by observing changes in occupancy concomitant with small changes of price. In our Value Pricing Pilot(VPP) Program study, called FlexPassPlus [1], we have used a new method to measure this quantity . By setting up repeated 2nd price auctions via an app we were able to get a lot more information about elasticity than through a traditional change-the-price-and-see-what-happens experiment. This leads to a better understanding of the parking incentive response curve. The parking incentive elasticity is estimated as 0.514 while intensity as -3.066. We find that the elasticity stays invariant but the intensity varies with weekday and weather.

KEYWORD: Parking Demand Management; Incentives Response Curve; Elasticity; Second Price Auction

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INTRODUCTION

76% of America's labor force drives alone to work (10). 95% of this cohort then parks in space provided by the employer below the market price or for free (7, 13). Charging the employee to park, or paying her to not park, can alter her preference for driving alone (15). Policy-makers use the parking price or incentive response curve to decide how much to charge or pay (4, 9). This curve is usually measured by observing changes in parking consumption concomitant with small changes of price (12). A confounding factor may change with the price and also influence levels of parking demand, e.g. weather and big events. The effect size of the price change in a before-after study can be profoundly affected by which confounding factors are controlled and the way this is done (3). This paper proposes and validates a new method revealing the amount employees must be paid, i.e., incentivized, to alter the preference for driving alone. The method is a repeated 2nd price reverse auction. We use the Becker-DeGroot-Marschak (BDM) mechanism (1). It is a reverse auction because subjects ask each day for the amount they want to receive to relinquish the privilege to park on university property, as opposed to the amount they are willing to pay for the privilege. The auction is repeated because each subject is invited to play each day for 61 days. UC Berkeley has 2958 employees who sometimes, or always, prefer to drive and park on university property. Our method is validated by application to 215 subjects from this cohort over a 3 month period. We show the method is able to discover the parking incentive response curve. We also show the known and heavy overhead of repeated bidding can be removed by a lightweight IT system compressed of apps on iPhone and Android and a server in the cloud.

Understanding the sensitivity of parking demand to changes in price or incentive has important implications for policies related to reducing congestion and emission. Parking price elasticity, one of the sensitivity measures, has been studied extensively in the literature. Price elasticity is defined as the percent change in the quantity of parking demanded divided by the percent change in the price. Elasticity is often estimated by observational studies and before-after experiments. In an observational study, the variation of parking price and occupancy is observed within a certain region. Elasticity is then estimated based on discrete choice models. Gillen (1978) used data from the 1964 Metropolitan Toronto and Regional Transportation Study to estimate a set of logit models (5). The elasticity measure of auto use with respect to parking costs was found to be -0.31. Analyzing observed and estimated responses to parking fees, Vaca and Kuzmyak (2005) estimates elasticity of parking demand to price in the range of -0.1 to -0.3 (14). The paucity of observed parking market responses was noted in the TRACE (1999) study of transport elasticities (2). One of the conclusions was to note that since 1985 almost all elasticities (transport related) have been generated by some form of modeling and that empirical responses ex ante and ex post of a price change were 'virtually absent' (8).

Recent parking elasticity estimates are mostly based on before-after experiments, where elasticity is estimated by observing changes in occupancy concomitant with small changes of price. Kanafani and Lan (1988) estimates parking price elasticity by regression based on the results of a series of price changes that took place at San Francisco airport (6). The demand functions estimated imply a wide variation in parking price elasticity (from -3 to -0.30). Kelly and Clinch (2009) measured price elasticity in the on-street parking market in Dublin city center when faced with a citywide increase in the hourly cost of on-street parking of 50% (8). By collecting the occupancy data before and after the price change, the average elasticity of demand is -0.29. Pierce and Shoup (2013) measured price elasticity in the SFPark study, where the meter rate changes based on occupancy rates (12). Price elasticity has an average value of -0.4, but varies greatly by time of day, location, and several other factors (from -0.98 to +0.05).

In taking the approach of ex ante and ex post demand analysis for the generation of price elasticities, attention was needed for extraneous confounding factors. A confounding factor may change with the price and also influence levels of parking demand, for example weather and big events. The wide range of price elasticities in Kanafani and Lan (1988) and Pierce and Shoup (2013) suggests that many variables other than price affect parking demand. Pierce and Shoup (2013) found that the price elasticity was positive in many cases. So other factors must have overwhelmed the effects of prices on parking demand. As the natural of before-after study, these confounding factor are often hard to measure and control. Kelly and Clinch (2009) considered fiscal and income changes. They pointed out that significant methodological challenges remain in controlling for other potential confounding factors when using revealed preference data to test the market response to changes in parking pricing.

This paper begins with a description of the experimental design, followed by a description of the subjects socio-economic characteristics. We then discuss the auction mechanism design and prove it is truth-revealing. App and the data collection system is introduced. We then describes the collected data and how to convert WTA data to daily incentive-response curves. Parking incentive elasticity and intensity is estimated.

EXPERIMENTAL DESIGN

Most employers offer free or underpriced parking to employees even as they feel the pressure to reduce the number of employees driving alone to work. Parking incentive is effective in these employer owned or leased lots. It is a better strategy than direct parking charges at employment sites where a move to paid parking is likely to cause significant employee morale issues or where management, for whatever reason, is unwilling to ask employees to pay for parking. The FlexPassPlus study described in this paper, explores a new kind of method to measure employee's incentive response curve. This observational study targets the current annual Central Campus **C** Permit and Faculty/Staff **F** Permit holders in UC Berkeley. UC Berkeley is the largest East Bay employers with 23,962 employees and 5,728 parking spaces. **C** and **F** permit holders constitute the vast majority of the regular users of campus parking. These parking permits allow holders to seek a parking space in parking garages or surface lots segmented by permit type. **C** permits are available only to faculty and senior staff, **F** permits to other staff. Subjects were recruited from the 4272 employees who had already purchased a **C** or **F** permit for the entire 2015 Fall semester. The study is conducted in the fall semester of 2015. The instruction days are from Aug. 24 to Dec. 11, 2015. The study covered three months in that period, from Sept. 1 to Nov. 30, 2015. During the study, the price for **F** permit was \$95 per month while \$131 per month for **C** permit. Study subjects would be able to anticipate daily second price auctions for 61 workings days during the study period.

Bidding every day for three months is a heavy task for subjects. We designed the reserve auction based on the Becker-DeGroot-Marschak(BDM) method. The bid is compared to a incentive determined by a random number generator. If the subject's bid is lower than the incentive, he or she receives the incentive and sells the parking privilege. If the subject's bid is greater than the incentive, he or she receives nothing and sells nothing. Subjects bid against random numbers instead of unknown bidders. This speeds up the auction process. We also build up a smart-phone based data collection system to make bidding more convenient for our subjects.

Participant Recruitment

All subjects were compensated with a \$25 Amazon gift card on completion of the sign-up process, installation and activation of the app. All subjects completing the study by filling out an exit survey were compensated the same amount. Thus most subjects received \$50 in Amazon gift cards in two installments. Among the 2958 C & F permit holders at UC Berkeley we reached through emails and postcards, 215 respondents finished the sign-up process to become subjects. Table 1 summarizes their demographic and socio-economic information. UC Berkeley staff make up the bulk of the sample. Most subjects are over 25 and under 65 years old. 42.2% of the subjects have at least one bike while 38.5% have a Clipper card which is a reloadable contactless card used for electronic transit fare payment in the San Francisco Bay Area. Sampling bias may exist as subjects are self-enrolled. It is checked in terms of the permit type distribution. There are 163 F permit holders within our 215 subjects, 75.8%. The total number of F permit holder population is 1999, 67.6% of the whole C & F permit holders. A Fisher test results in a p-value of 0.012. The sample selection bias is significant. More F permit holders are enrolled in the study compared to the permit holder population.

Auction Procedures

Study subjects are requested to download and install the FlexPass-Plus app for their phone. Upon installation of the application, subjects will have the opportunity to sell their parking on campus each working day (Mon. to Fri.) during the study period. Subjects can ask to be paid any amount up to \$15 to sell their parking on campus for the day. After the subject submits his or her ask, the app will pick a random amount as market price, uniformly generated, between \$0 and \$15. If the random amount is greater than or equal to the ask, the subject wins and the bid is accepted at the random number. The research team will credit that random amount to the subject's account and the subject will not be able to use his or her permit to park on campus that day. If the random number is less than subject's ask or the subject did not participate for the day, he or she is allowed to park on campus. Figure 1(a) shows the auction interface. To avoid the default effect, the default bid is set at \$ 15. If subjects want to sell parking, they must move the slider to bid. The App will also prompt the subject to report the mode he or she will use to get to campus or not coming at all. Figure 1(b) shows the interface for travel mode report. For example, if you are a permit holder and submit that you want to sell your parking access for Nov-11-2015 at \$3. Since the probability of any number generated between \$0 and \$15 is equal, the probability of you winning, i.e. your price being less than the random number and hence accepted is 80%. The

TABLE 1 : Sample descriptive statistics

	Study Subject Count	(%)	**Permit Holder** Count	(%)
Permit Type				
F	163	75.8	1999	67.6
C	52	24.2	959	32.4
Employment Status				
FACULTY FULL TIME	57	26.7		
FACULTY PART TIME	3	1.2		
STAFF FULL TIME	150	69.6		
STAFF PART TIME	5	2.5		
Age Group				
18 - 24	3	1.2		
25 - 34	31	14.3		
35 - 44	60	28.0		
45 - 54	65	30.4		
55 - 64	33	15.5		
65 AND OLDER	8	3.7		
NOT REPORTED	15	6.8		
Income Group				
40 AND LESS	1	0.6		
41 - 60	23	10.6		
61 -80	57	26.7		
81 - 100	37	17.4		
101 - 120	27	12.4		
121 AND MORE	51	23.6		
NOT REPORTED	19	8.7		
Gender				
FEMALE	116	54.0		
MALE	83	38.5		
NOT REPORTED	16	7.5		
Has Bike				
FALSE	124	57.8		
TRUE	91	42.2		
Has Clipper Card				
FALSE	132	61.5		
TRUE	83	38.5		
Total Number				
	215		2958	

higher your price is, the less chance you will win. However, if your price is too low, you may end up taking transit to campus with only \$1 compensation. The best strategy is to bid the amount your truly willing to accept to forgo parking. For example, it may cost you \$10 to take transit (say \$5 for ticket and \$5 for the other costs, such as extra travel time and walking). Then submitting your price at \$10 maximizes your net benefit. The chart in figure 1(c) illustrates the procedure for selling parking access and possible outcomes.

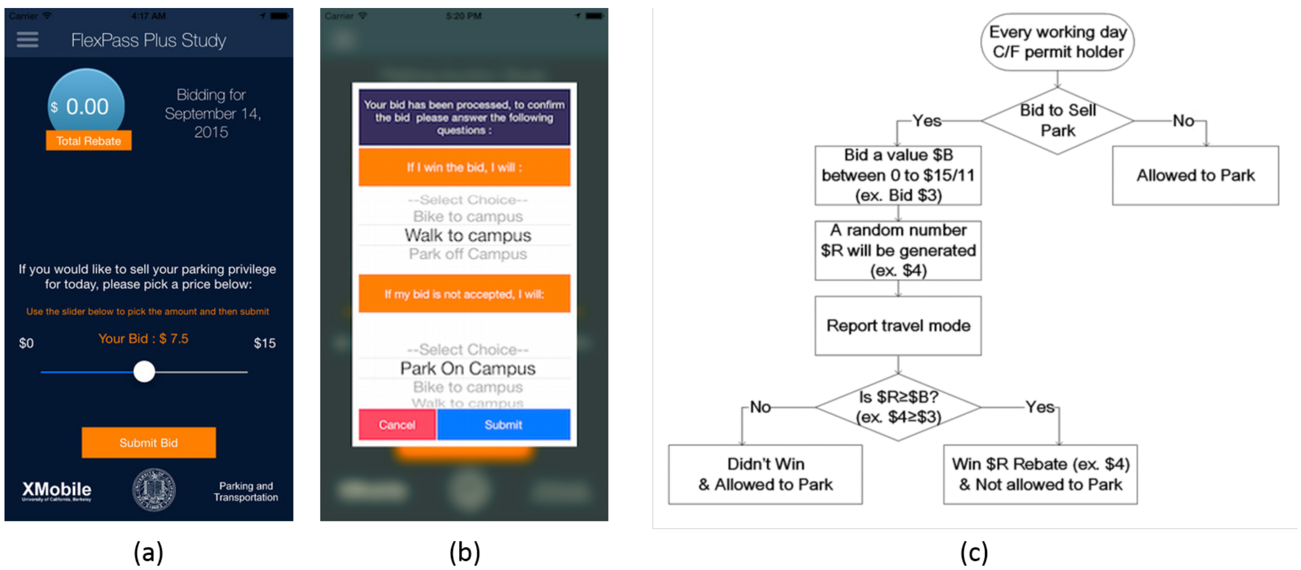

FIGURE 1 : App screens and auction flow chart

Subjects' responses regarding whether or not they are parking on a given day are uploaded to the server through the FlexPassPlus app and sent to parking enforcement officers. If subjects sell their parking access, but park on campus, they would potentially receive a parking citation. Subjects can bid on the following day starting at 12:01 pm. The auction ends at 12 pm of that day. The 12 pm is chosen because most employees commute to campus before 12 pm. It ensures enough time for subjects to make commute decision and bid. Once subjects submit their ask for a given day, subjects cannot change it or participate again. It is designed for truth revealing. If a subject haven't bid for the next day by the previous evening at 6 pm, he or she receives a notification on the phone reminding the subject to do so.

Auction Mechanism

Let $u(m,i;X)$ denotes the utility of commuting for a certain subject on a certain day. m is the travel mode which takes value from the choice set M. M contains all the possible travel modes and the choice of not commuting, $M = \{\text{PC, NO-COMMUTE, BIKE, ...}\}$. PC denotes park on campus. i is the incentive received in dollar value. Assume u is increasing in i, $\frac{\partial u}{\partial i} > 0$ (monotone assumption). X captures all other features related to travel behavior, e.g. age, income and weather. Define the alternative modes set $A = M/\{\text{PC}\}$. The WTA to forgo parking with alternative mode $a \in A$, denoted as $\widetilde{V}(a;X)$, is then defined by the following:

$$u(PC,0;X) = u(a,\widetilde{V}(a;X);X)$$

It means that provided a $\$\widetilde{V}(a;X)$ incentive or above, the subject is willing to change from parking on campus to alternative mode a.

Consider a general set up of our second price auction. Subject can ask for a price B between \$0 to $\$\bar{\theta}$. After that a random number R will be generated. Denote the p.d.f. of R as $f(.)$. $f(R) > 0$ for $R \in [0, \bar{\theta}]$. If $R \geq B$, the subject will win \$R and loss the privilege to park on campus. In this case, the subject's benefit W is $u(a, R; X) - u(PC, 0; X)$. If $R < B$, the benefit will be 0. The expected value of benefit W is:

$$E[W|B, a, X] = \int_{B}^{\bar{\theta}} [u(a, R; X) - u(a, \widetilde{V}(a; X); X)] f(R) dR$$

Everyday, The subject will make three decision: 1) decide whether to anticipate the auction or not; 2) choose the alternative mode if the privilege of parking were sold (choose a from A); 3) place an ask (choose ask ,B, from $[0, \bar{\theta}]$). First, for any given a, we will prove the dominate strategy for the subject is to ask a price of $\widetilde{V}(a;X)$. We will then focus on how to choose the optimal a.

For fixed a, we find a $B \in [0, \bar{\theta}]$ to maximize $E[W|B, a, X]$. Checking the first order condition, we get $B^*(a;X) = max\{min\{\widetilde{V}(a;X), \bar{\theta}\}, 0\}$ (detailed proof is attached in the appendix). If the WTA to forgo parking with alternative mode a is within the range of $[0, \bar{\theta}]$, the dominate strategy is to place the bid at the value of true WTA, $\widetilde{V}(a;X)$. If $\widetilde{V}(a;X)$ is greater than $\bar{\theta}$, the subject cannot benefit from the auction. In this case, the subject will bid $\bar{\theta}$ or not anticipate the auction. If $\widetilde{V}(a;X)$ is less than 0, the subject prefers to commute with other modes rather than park-on-campus. For example, some permit holders bike to campus for health benefits. The subject will bid \$0 to collect the maximal rebate. The subject's ask, B, provides a monetary standard for the difference between park-on-campus and alternative mode a.

We make a further assumption of the form of the utility function. Assume $u(m, i; X)$ satisfies the following property: u(m, i; X) = u_m(m; X) + $u_i(i;X)$ (additive separability assumption). u_m is the utility associated with mode and u_i is the one associated with incentive. Additive separability assumes that incentive i has the same influence on overall utility across all commute modes. The value of parking V(X) is then defined as

$$V(X) = \min_{a \in A} \widetilde{V}(a;X)$$

V(X) is also the minimal amount the subject would accept to forgo parking under condition X. Define $a^*(X) = \arg\min_{a \in A} \widetilde{V}(a;X)$. Under monotone and additive separability assumption, $a^*(X)$ dominates all other modes in choice set A. $a^*(X) = \arg\max_{a \in A} u(a, i; X)$ for all incentive level i.

After placing the optimal ask $B^*(a;X)$, the net benefit becomes a function of a and X. Apply additive separability assumption:

$$\Omega(a;X) = \max_{B \in [0, \bar{\theta}]} \{E[W|B, a, X]\} = \int_{B^*(a;X)}^{\bar{\theta}} [u_i(R;X) - u_i(\widetilde{V}(a;X);X)] f(R) dR$$

where $\Omega(a; X)$ is the expected net benefit of choosing alternative mode a. Apply monotone assumption, it easy to check the dominate alternative mode $a^*(X)$ maximize $\Omega(a; X)$.

In the second price auction of our study, a rational subject will bid $V(X)$, which is the value of parking. The subject will also report the alternative mode when not parking on campus. The reported alternative mode is the most preferred alternative mode, $a^*(X)$. For example, a subject bid \$10 and reports that he or she will take transit if wins the auction. Otherwise he or she will park on campus. We can extract the following information: 1) the subject is indifferent between park-on-campus and transit+\$10; 2) among all alternative modes, the subject prefer transit the most. The former one is based on the monotone assumption. The later one is based on both monotone and additive separability assumption.

Software System for Data Collection

A smartphone based software system, shown in Figure 2, is designed to collect WTP to forgo parking. The production server is a firewall protected Virtual Private Server hosted by UC Berkeley IST in their cloud infrastructure. The server executes an off-the-shelf openSuSE Linux version 13.1. The main server components are the Apache HTTP server, the Apache Tomcat server and the PostgreSQL database. Location data are collected from the subjects via the smartphone app. The data transfer between smartphone app and server is protected by encryption and authentication. Each subject has her own username and password to access the server via the smartphone app. The server exposes only the ports Secure Shell (SSH) within the UC Berkeley Campus and Web Server (HTTP/HTTPS). Access to the unsecured HTTP port of the Web Server is automatically redirected to the encrypted HTTPS port. No other service, especially the database, is directly accessible from outside the server.

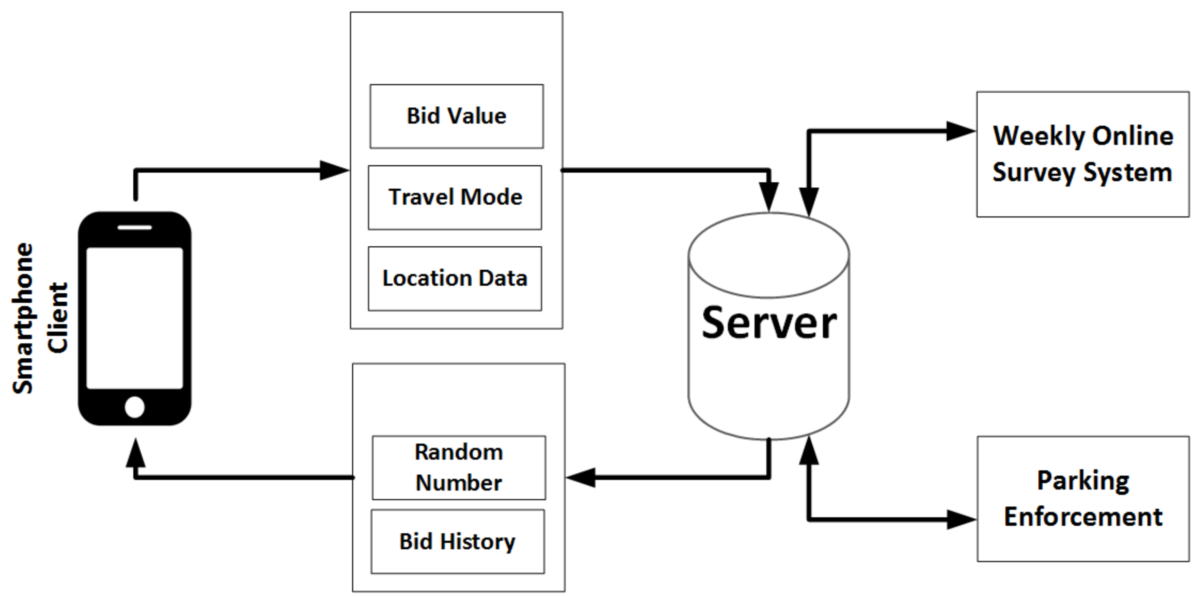

FIGURE 2 : Software system for data collection

DATA DESCRIPTION

During the three month study period, on every day, 215 subjects may decide whether to anticipation the auction or not. If subject i bids to sell his or her parking on day j, a bid value, b_{ij}, will be recorded. The subject will also report the commute mode if he or she wins the auction, $m_{w,ij}$, and the mode if losses, $m_{l,ij}$. If the subject does not bid, it is considered as his value of parking on this day is greater than $15.

Do Subjects Understand the Mechanism?
Subjects can be divided into two groups by their reported loss-mode $m_{l,ij}$. If the loss-mode is Park-on-Campus, it means that parking is needed and the WTA to forgo parking is positive. We name this group as Lose-Park group. Otherwise, even without any incentives the subject will not park on campus, e.g. the subject plans to stay at home on that day. We name this group as Lose-NoPark group. If subjects understand the auction rules and bid rationally, they should submit bids close to zero when reporting not park on campus even if losing the auction. For the other group, whose loss-mode is Park-on-Campus, they should bid a positive amount. Violin plots in the above part of figure 3 shows the bid distribution of the two groups for each day. The violin plot is similar to box plots, except that they also show the probability density of the data at different values. The bold bar shows the median of the bids. Different widths at different bid values represent the kernel density estimation. For the first several days during the study, the bid distribution of two groups overlaps each other. The blue bar, median bid of Lose-NoPark group, is close to the red bar, median bid of Lose-Park group. It shows that in the first week subjects were confused by the rules and submitting meaningless bids. After Sep. 8, the second week, the blue bar began significantly lower than the red bar but still away from zero. Some subjects started to figure out the optimal biding strategy and bid small amounts when they do not need to park. On Oct. 7, one month since the beginning of the study, the blue bar is still significantly higher than zero. We decided to intervene. An email survey was sent out to every subject with what we called 'Hawaii Treatment'. In the treatment, the following question was asked: 'Imagine you are on vacation in Hawaii on next Monday, what would you bid to sell your parking privilege for that day?'. The question is followed with a slier bar ranging from $0 to $15. The optimal bid is $0 as parking will have no value to the subject if he or she is on vacation off campus. If the subject bids above $2, he or she will see on the next screen: 'You are leaving money on the table'. We will explain the auction rules again, emphasizing that the subject is biding against a random number. The above part of figure 3 shows that after the Hawaii treatment, the blue bar became close to zero and it continued to the end of the study. It is considered as most subjects understood the auction rule and were biding their true value of parking. The following of this paper will only analyze the data collected after the Hawaii treatment, from Oct. 8 to Nov. 30. The below part of figure 3 shows the number of subjects anticipate the auction every day. There are 23% subjects anticipating the study every day on avergae and no significant drop-out being observed.

Bid value should also be affected by the alternative mode. It is shown in table 2. Row names stand for win-modes while column names for lose-modes. Number after the $ sign shows the median bid. Number in the bracket shows the number of bids under a certain win-mode and lose-mode pair, $\{m_{w,ij}, m_{l,ij}\}$. For instance, during the study, subjects reported 773 times that they will not commute no matter win or not. The median bid of these 773 bids is $0.5. Subjects reported 132 times that they will park on campus if losing the auction and not commute if winning the incentive. The median bid of these 132 bids is

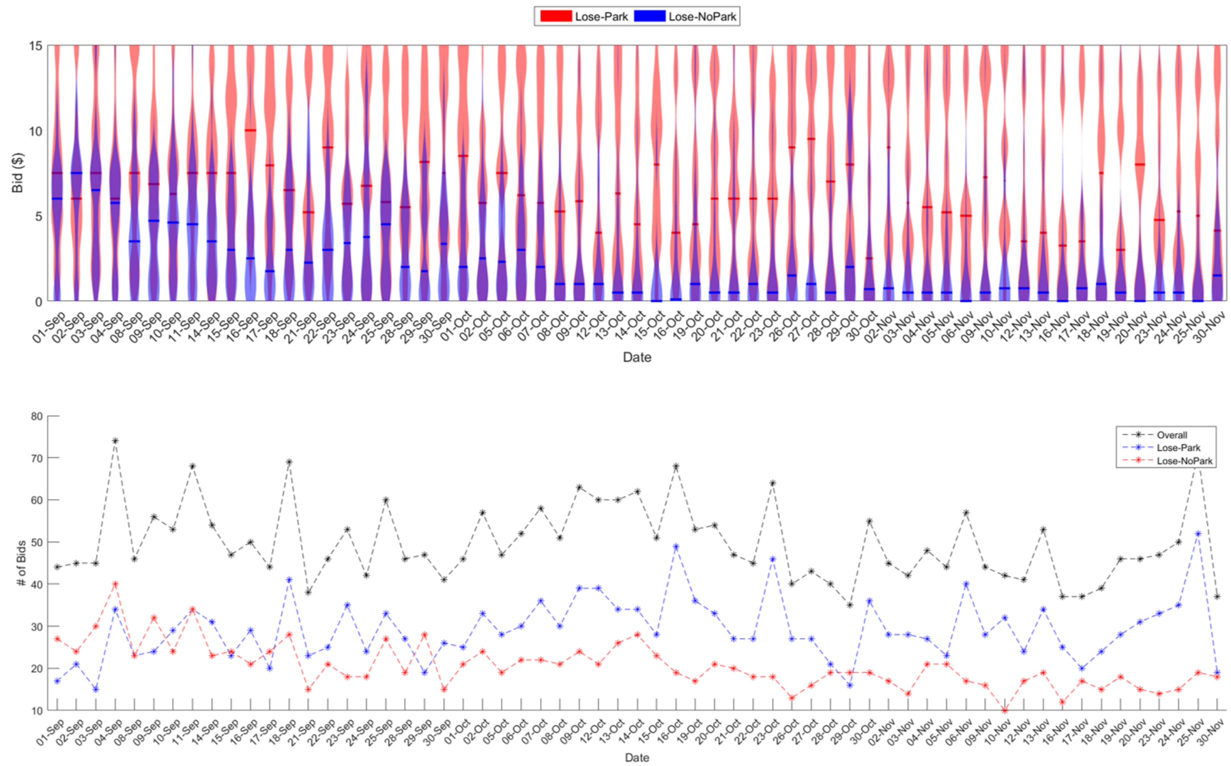

FIGURE 3 : Bid distribution and anticipation

$2.25. The difference indicates the value of parking when alternative mode is Not-Commute, $\widetilde{V}(\text{No-Commute}; X)$. It can be observed that most bids occurred in diagonal cells, where $m_{w,ij} = m_{l,ij}$, and the last row, where $m_{l,ij} = \text{PC}$. Bids in diagonal cells are close to zero. Focusing on the last row, when the alternative is Transit, the median bid rises to $9.5. The difference between $9.5 and $2.25 may reflect transit ticket price and the value of extra walking time, which requires further investigation and is beyond the scope of this paper. Table 2 again indicates that subjects understood the mechanism and bid their true WTA to forgo parking in the study.

Direct Measure of Incentive Response Curve

A fundamental input to any incentive and revenue optimization analysis is the incentive-response curve (or function). The incentive-response curve specifies parking demand reduction as a function of the incentive level. By collecting WTA from each parking permit holders, the incentive-response curve can be measured directly in our study.

The empirical distribution of bid values is shown in figure 4, where the x-axis is bid value and y-axis is empirical cumulative distribution function (c.d.f.). Different colors represent different weekdays. As subjects are biding their true WTA to forgo parking, figure 4 is also the incentive-response curve, where x-axis can be named as incentive rate, I, and y-axis percentage of subjects not park on campus, $S(I)$. For example, on an average Friday, 20% percent subjects bid under $5. It also means that if offered a $5 incentive on Friday, 20% percent subjects will accept it and forgo parking. If the same reduction need to be achieved on Thursday, the incentive level should be raised to $ 10.5. The power of incentive,

TABLE 2 : Bid Value and Commute Mode.
(Row names are for win-modes while column names are lose-modes. Number after the $ sign shows the median bid. Number in the bracket shows the number of bids.)

	NO COMMUTE	OTHER TRANSPORT	TRANSIT ONLY	BIKE AND TRANSIT	PARK OFF CAMPUS	CARPOOL	BIKE	WALK
NO COMMUTE	$0.50 (773)	-	$9 (1)	$0.50 (1)	$9.50 (3)		$2 (2)	$3.50 (1)
OTHER TRANSPORT	$1 (2)	$2 (29)						
TRANSIT ONLY			$0.25 (84)			$0 (1)		$2.5 (1)
BIKE AND TRANSIT	$1.5 (1)		$0.5 (1)	$0.5 (19)				
PARK OFF CAMPUS	$3.25 (6)	$9 (1)	$11.5 (1)		$6.5 (60)	$1 (5)		$7.5 (1)
CARPOOL		$0.5 (1)			$1 (1)	$1 (29)		
BIKE	$3.25 (1)	$13.5 (1)					$2 (19)	
WALK		$10 (1)						$1.5 (44)
PARK ON CAMPUS	$2.25 (132)	$4.5 (8)	$9.5 (130)	$4 (23)	$8 (226)	$2.5 (23)	$5 (64)	$3 (31)

parking demand reduction induced by incentive, can be extracted from the response curve. The percentage of subjects not park on campus under \$0 incentive, $S(0)$, serves as baseline. The difference, $S(I)-S(0)$, is the demand reduction, named as $R(I)$. It can be observed that Friday's curve is significantly higher than curves of other weekdays. For UC Berkeley, most courses are scheduled through Monday to Thursday. Friday is for discussions and group meetings. Thus subjects have more flexible schedules. Figure 4 gives insight into incentive scheme design. Subjects react to incentives in different ways on different weekdays. Thus setting different incentive rates based on weekdays could be a better optional then offering a flat rate. The next section will further explore the demand reduction function, $R(I)$, by building up explanatory models.

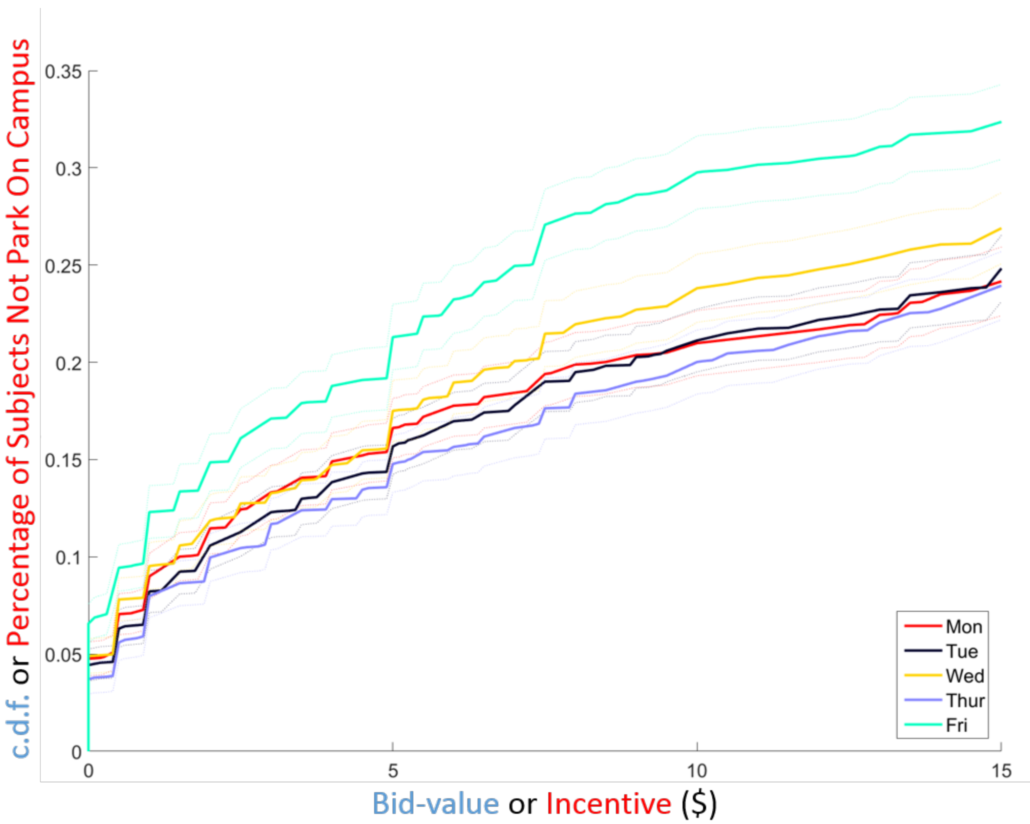

FIGURE 4 : Bid distribution or incentive-response curves

PARKING INCENTIVE RESPONSE CURVE

We assume the elasticity of parking consumption to incentive to be constant, as in the literature relating parking consumption to price (8, 12). This yields the equation

$$\log R_{jk} = \alpha + \beta \log I_{jk} + \varepsilon_{jk} \tag{1}$$

where β is parking incentive elasticity and α is intensity. I_{jk} is the incentive rate at level k on day j. $k = 1, 2, ..., 60$ and $I_{jk} = k/4$. I_{jk} takes value from \$0.25 to \$15 with step size \$0.25. R_{jk} is the observed demand reduction under I_{jk} on day j. Precisely, $b_i j$...

$R_{jk} = \sum_i 1\{b_{ij} \leq I_{jk}\}/N - \sum_i 1\{b_{ij} = 0\}/N$ where N is the total number of subjects. The minuend, $\sum_i 1\{b_{ij} < I_{jk}\}/N$, is the percentage of subject relinquishing parking for incentive I_{jk}, $S_j(I_{jk})$. The subtrahend, $\sum_i 1\{b_{ij} = 0\}/N$, is the percentage of subjects not parking on campus on day j regardless of incentive, $S_j(0)$.

The first row of figure 5 shows daily incentive response curves. There are 61 curves, one for each working day in the study period. They are grouped by the day of the week. The second row shows daily log-incentive v.s. log-reduction curves. It can be observed that the incentive-response curves vary a lot but the log-reduction v.s. log-incentive curves share a similar shape, linear. The red lines are ordinary least square (OLS) fits using regression equation 1. In the OLS regression, we assume the noise term ε_{jk} is i.i.d. across different incentive levels and days. However, figure 5 shows that the gray curves in log-log space enjoy the similar slope but differ in their intercepts. The multiple demand reductions measured on the same day could be correlated. Therefore, we modify equation 1 to a mixed linear model,

$$\log R_{jk} = \alpha + A_j + \beta \log I_{jk} + \varepsilon_{jk} \tag{2}$$

where α is the average intensity for all days, and A_j a day-specific deviation from α. We first assume A_j is a fixed effect, a constant for day j. F test between a fixed effect model and OLS regression is conducted. The test indicates significant fixed effect with p-value less than 0.01. We then assume A_j is a random effect, a realized value of a random variable, and it is uncorrelated with the independent variable. Hausman test is conducted between random effect and fixed effect model. The p-value is 0.961. We cannot reject the null hypothesis that two models are consistent. Random effects (RE) is preferred due to higher efficiency.

Regression result is shown in table 3. There are four models, baseline-model, weekday-model, weather-model and weekday-weather model. The baseline regression equation is shown in equation 2. The regression equation for the weekday-model is

$$logR_{jk} = \alpha_0 + \alpha_{Weekday} Weekday + (\beta_0 + \beta_{Weekday} Weekday) \log I_{jk} + A_j + \varepsilon_{jk}$$

where $Weakday$ takes value from Monday to Friday. 4 dummy variables are used to sort it into mutually exclusive categories. $Friday$ serves as the baseline. α_0 and β_0 represents the intensity and elasticity on Friday. $\alpha_{Weather}$ and $\beta_{Weather}$ describes the difference in intensity and elasticity on other working days. The weather model regression equation is

$$logR_{jk} = \alpha_0 + \alpha_{Weather} Weather + (\beta_0 + \beta_{Weather} Weather) \log I_{jk} + A_j + \varepsilon_{jk}$$

where $Weather$ has two categories $Clear$ and $Cloudy\ or\ Rainy$. One dummy variable, $1\{Weather = Cloudy\ or\ Rainy\}$, is used in the regression. $Clear$ is the baseline. α_0 and β_0 represents the intensity and elasticity on a clear day. $\alpha_{Weather}$ and $\beta_{Weather}$ represents the difference in intensity and elasticity on a cloudy or rainy day. The full model, weekday-weather model regression equation is

$$\begin{aligned} logR_{jk} = {} & \alpha_0 + \alpha_{Weekday} Weekday + \alpha_{Weather} Weather \\ & + (\beta_0 + \beta_{Weekday} Weekday + \beta_{Weather} Weather) \log I_{jk} + A_j + \varepsilon_{jk} \end{aligned}$$

Confounding factors in a before-after study, such as weather, are used as dependent variables in our regression. We measure the WTA for each subject. Based on the WTA data, we construct 61 incentive response curves, one for each day in the study period. For all the days, the incentive level I_{jk} takes the same set of values, from \$0.25 to \$15 with \$0.25 increment. The $Weather$ variable has different value on different days but the incentive level I_{jk} is also independent to $Weather$. That makes the elasticity estimation free of confounding. The estimation result of this baseline random effect model is shown in first column of table 3. The average parking incentive elasticity is 0.514. With 1 percent increase in the incentive, parking demand will reduce by 0.514 percent on average. The elasticity is positive as expected. The 95% confidence interval is from 0.504 to 0.524, which indicates that the elasticity estimate is efficient. The elasticity is also significantly less than 1, rendering our incentive response inelastic (11). The average parking incentive intensity is -3.066 with standard deviation 0.038. Intensity can be interpreted as the baseline demand reduction. $exp(\alpha)$ represents the average parking demand reduction under incentive level \$1. $exp(-3.066)$ equals 4.66%.

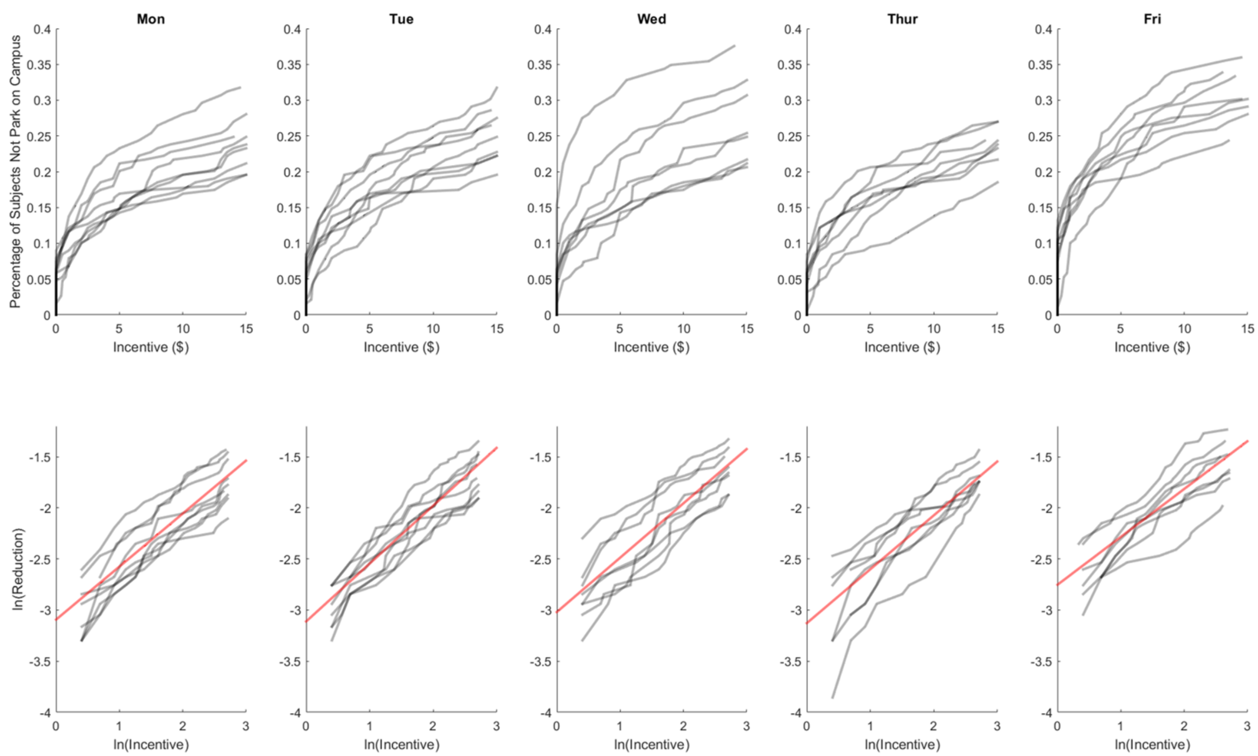

FIGURE 5 : The first row shows incentive-response curves for every day divided by weekdays. Each curve stands for a day in the study. The second row shows log-reduction v.s. log incentive. The red line is the ordinary least square fit.

Figure 4 and 5 shows that incentive-response curves differ by weekdays. Second column in table 3 illustrate the estimation of demand reduction curve after taking weekday into consideration. Friday serves as baseline, with a elasticity of 0.489 and intensity of -2.877, $exp(-2.877)$=5.63%. The elasticity on other weekdays is close to the Friday one. The elasticity of Monday and Thursday is significantly higher but the difference is small, around 0.05. The intensity on other weekdays is lower than Friday's. Likelihood ratio test shows that the model with weekday effect is significantly improved from the baseline model in column (1). Column 3 of table 3 evaluates the effect of weather on the incentive-response function. Likelihood ratio test shows that the model with weekday and weather effect is significantly improved from the baseline model in column 1. We expected that subjects had a hard demand of parking on bad weather day. Hence the elasticity on rainy days should be lower. However, the regression shows that subjects are more sensitive to incentives on cloudy or rainy days. Compared to clear weather day, on cloudy or rainy day elasticity is significantly higher by 0.073. The full model that accounts both weekday and weather effects is shown in column (1) of table 3. Likelihood ratio test shows that the full model is significantly improved from the model with only weekday or weather effect. Comparing to Weekday-Model, The difference of elasticity between Monday and Friday is no longer significantly. The difference is captured in weather condition instead. Compared to clear day, on cloudy or rainy day elasticity is significantly higher by 0.084. Compared to clear weather day, intensity on cloudy or rainy day is significantly lower by 0.332. On clear weather Friday, with \$10 incentive, the median demand reduction is estimated as $exp(-2.877 + 0.489 * ln(10)) = 17.36\%$. On cloudy Friday, this number is $exp[-2.877 - 0.334 + (0.489 + 0.084) * ln(10)] = 15.08\%$. As incentive rate rises, the difference will become smaller. At \$15 rate, the demand reduction under clear weather becomes $exp(-2.877 + 0.489 * ln(15)) = 21.17\%$. On cloudy day this number is $exp[-2.877 - 0.334 + (0.489 + 0.084) * ln(15)] = 19.03\%$. Although the elasticity on cloudy day is higher, the difference in the intensity is much greater, which dominates the overall trend and makes incentive less effective on bad weather days.

The first row of Figure 5 illustrates the heterogeneity of parking demand reduction. Regression model in table 3 shows that parking incentive elasticity stays rather constant under various weekday and weather conditions. However, parking incentive intensity varies a lot, which accounts for the variation in parking demand reduction.

CONCLUSION

We designed the FlexPassPass study to measure the parking incentive-response curve. Subjects in the study enter a willingness-to-accept bid to sell their parking privilege everyday. A repeated second price reverse auction is deployed. Our system has the advantage of learning much more about incentive elasticity than through the more traditional approach of changing prices and observing reactions. We also build up the IT system to make bidding more convenient for our subjects. The smartphone app contains the features of bidding with 2 clicks, commute mode report, rebate summary and daily reminder of bidding. During 3 month period, the participation rate is above 20% for most days and there is no significant trend of drop-out. We estimate the parking incentive elasticity as 0.514 while intensity as -3.066.

Compare to before-after studies in the literature, the incentive-response curve is measured separately for each day. Confounding variables in the before-after study, such as weather condition, can be used as explanatory variable in the FlexPassPlus study. We find that the elasticity stays rather invariant but the intensity varies with weekday and weather.

TABLE 3 : Incentive-response Curve Regression Results

	Dependent variable: log_reduction			
	(1)	(2)	(3)	(4)
	Baseline	Weekday	Weather	Weekday-Weather
Elasticity				
log_incentive	0.514***	0.489***	0.500***	0.489***
	(0.005)	(0.011)	(0.005)	(0.011)
log_incentive : Weekday(Fri)				
Mon		0.047***		0.002
		(0.015)		(0.016)
Tue		0.010		−0.013
		(0.016)		(0.016)
Wed		0.024		0.013
		(0.016)		(0.015)
Thur		0.044***		0.044***
		(0.016)		(0.015)
log_incentive : Weather(Clear)				
Cloudy or Rainy			0.073***	0.084***
			(0.012)	(0.014)
Intensity				
Constant	−3.066***	−2.877***	−3.002***	−2.877***
	(0.038)	(0.083)	(0.040)	(0.082)
Weekday(Fri)				
Mon		−0.314***		−0.142
		(0.114)		(0.124)
Tue		−0.199*		−0.106
		(0.118)		(0.119)
Wed		−0.106		−0.060
		(0.118)		(0.116)
Thur		−0.306***		−0.306***
		(0.118)		(0.115)
Weather(Clear)				
Cloudy or Rainy			−0.332***	−0.334**
			(0.091)	(0.103)
log likelihood	716.16	727.08	736.60	747.27
Df	4	12	6	14
AIC	-1424.3	-1430.2	-1461.2	-1466.5
Note:				*p<0.1; **p<0.05; ***p<0.01

The elasticity of Thursday is significantly higher than other weekdays by 0.044. Compare to clear weather, the elasticity is significantly higher on cloudy or rainy day by 0.084. The intensity of Thursday is significantly lower than other weekdays by 0.306. Compare to clear weather, the intensity is significantly lower on cloudy or rainy day by 0.334. When incentive rate is in reasonable range, the variation of intensity is much higher and dominates the variation of elasticity.

In the long term the FlexPassPlus study offers some particular advantages, such as enabling a perfect match of parking supply and demand on each day, once people who seek daily parking are presented an opportunity to place their own bids.

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APPENDIX

The first derivative of $E[W|B,a,X] = \int_B^{\overline{\theta}} [u(a,R;X) - u(a,\widetilde{V}(a;X);X)]f(R)dR$ is:

$$[u(a,\widetilde{V}(a;X);X) - u(a,B;X)]f(B)$$

Given 0 $\leq$B$\leq$ $\overline{\theta}$, then three cases are discussed to develop the maximum value:

(i) when $0 \leq \widetilde{V}(a;X) \leq \overline{\theta}$, the maximum value is achieved at B = $\widetilde{V}(a;X)$. Since $u(a,B;X)$ increases in B, the first derivative of $E[W|B,a,X]$ is positive in [0,$\widetilde{V}(a;X)$] while negative in [$\widetilde{V}(a;X)$,$\overline{\theta}$];

(ii) when $\widetilde{V}(a;X) < 0$, the maximum value is achieved at B = 0, as the objective function decreases in [0, $\overline{\theta}$];

(iii) when $\widetilde{V}(a;X) > \overline{\theta}$, the maximum value is achieved at B = $\overline{\theta}$, as the objective function increases in [0, $\overline{\theta}$].

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