Title
Experimental Methods in Transportation Pricing: Applications to Employee Parking

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Publication Date
2018

Peer reviewed|Thesis/dissertation

Experimental Methods in Transportation Pricing: Applications to Employee Parking

by

Dounan Tang

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Engineering – Civil and Environmental Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Raja Sengupta, Chair
Professor Joan Walker
Professor Shachar Kariv

Fall 2018

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Abstract

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Professor Raja Sengupta, Chair

In this dissertation, we develop two experimental methods for the problem of pricing or incentivizing use of a transportation service and apply them to the pricing of employee parking at the University of California, Berkeley.

The University of California, Berkeley, with 23,962 employees is the largest employer in the eastern half of the San Francisco Bay Area and has a problem with employee parking. The university wants to explore a daily parking cash-out program, named the FlexPass, to make employees more mindful of their parking consumption. We use a Randomized Controlled Trial(RCT) to reveal the causal power of the cash-out. The RCT is applied to 392 employees, representing 10% of the university employees driving alone and parking, over three months using an IT system able to collect daily parking consumption, weekly commute mode reports and location data. The FlexPass treatment reduced consumption by 6.1% with high significance.

Our second experiment is focused on measuring an incentive response curve. We use a repeated 2nd price reverse auction, in which 215 parking permit holders participate for 61 working days. Our method measures the incentive response curve for our subjects and we estimate the curve for the employee population using a quantile regression. We find 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.

Finally, we build a two-stage signaling game and design a variable-rate daily incentive scheme, where the incentive changes based on weekday and weather. The variable-rate daily incentive outperforms the fixed-rate daily incentive on both parking cruising times and leftover parking spaces.

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Acknowledgments

Firstly, I want to thank my advisor, Prof. Raja Sengupta, for advising me. I would like to thank the rest of my thesis committee: Prof Joan Walker. and Prof. Shachar Kariv for their insightful comments and encouragement.

The research was supported in part by City of Berkeley, California as sub-awardee of Caltrans as sub-awardee of Federal Highway Administration #84753. I would like to thank the project manager, Allen Greenberg. I would like to thank colleges who build the software system for data collection: Ziheng Lin, Fadi A. Kfoury and Clemens Krainer. I would like to thank the director of the Parking and Transportation Department of University of California, Berkeley, Seamus Wilmot, the travel demand manager, Lauren Bennett, parking enforcement officers: Mario Villezar, Danny Parajon, Derek Spears and Bobby Scott and the admin-staff: Randall Pollard and Devika Anand.

I would like to thank my friends, Han Cheng, Yanqiao Wang, Lei Kang and Mogeng Yin, my labmates Zhilong Liu and Vishwanath Bulusu, for all the sleepless nights, fun and sorrows. I would like to thank my childhood friend, Xiaoran Hu, for cheering me up on the other side of the Atlantic ocean. I would like to thank my roommate, Xiaomeng Shi, for all the research ideas we come up together and the delicious food he cooked.

Last but not the least, I would like to thank my parents for supporting me spiritually, praising my every small accomplishment, and tolerating the rest. I would like to thank my grandparents for raising me, taking care of me and sharing their many years of experience and wisdom.

Chapter 1

Introduction

In this dissertation, we develop two experimental methods to solve the problem of measuring the demand curve and obtaining the right price or incentive for a transportation service, and we apply them to the pricing of employee parking at the University of California (UC), Berkeley. One method is the randomized controlled trial, which we use to measure the change in parking demand caused by a change in price. Our other method is a repeated second-price auction and we use it to measure a parking incentive response curve. Our experimental field is the campus parking at the University of California, Berkeley. With 23,962 employees, UC Berkeley is the largest employer in the eastern half of the San Francisco Bay Area and has a problem with employee parking.

Our interest in the problem of measuring or estimating price response curves is based on the ability of price or incentive programs, like priced lanes, parking cash-outs, or fuel tax increases, to reduce congestion, pollutant emissions, or energy consumption. The price or incentive response curve is a fundamental tool used in such programs to set prices, incentives and control demand. Any change in the price of a transportation service yields two points on the curve if one is able to estimate how much of the change in demand is caused by the change in price. We call such an analysis a before-and-after study. Estimating causation can be made difficult by extraneous factors, such as big events or weather, that are concomitant with the price changes. These can also change demand and bias estimates. Before-and-after studies of pricing programs like Minnesota Pay-as-You-Drive [1], California Parking Cash-Out [45], or Washington State Commute Trip Reduction programs [58], deal with this bias by modeling to control for confounding factors.

Our first contribution targets this confounding factor problem. We introduce a parking price change as a randomized controlled trial (RCT) [36], an experimental form structured by medical science to ease the problem of inferring which outcomes are clearly attributable to a treatment [38]. We adapt this idea to the problem of measuring how much of a change in demand is caused by a change in price. Subjects in an RCT are randomly divided into two groups, of which one receives a treatment (the new price) and the other does not. Any difference between the treatment and placebo groups is hypothesized to be caused by the treatment by virtue of the random assignment. A two-point price response curve based on an RCT with one point representing the control group and the other representing the treatment group, will be more accurate than the curve based on a before-and-after study, where one point would represent the consumption before the price change and the other after. Our RCT targets our university's interest in a daily parking cash-out program which should make employees more mindful of their parking consumption. We introduced the program as an RCT to a limited set of employees for 3 months, and collected the data. We analyze it in chapter 2 to infer how much of the change in consumption is caused by the cash-out. Our experiment is the FlexPass study of the Federal Highway Administration (FHWA)'s Value Pricing Pilot (VPP) program [51]. We use the RCT causation hypothesis to isolate the demand reduction due to the cash-out.

Analysis under the RCT hypothesis yields a significant finding. In the year 2015, UC Berkeley priced campus parking permits for faculty and staff between $95 and $131 per month, reserved 2,080 parking spaces for its 2,958 employee permit holders, and operated another 380 stacked parking spaces to meet excess demand. Field observations have shown occupancies to be above 85% at most parking lots for much of the workday [39]. Our RCT recruited 392 of these parking permit holders and randomly assigned them to a treatment or control group. All subjects were incentivized with Amazon gift cards to report their commute mode daily using a smartphone app and weekly email surveys, enrolling in the study, and completing the entry and exit surveys. Subjects in the treatment group also receive the university's FlexPass as incentive and collect cash-outs based on the number of days they forgo parking. Section 2.3 argues that the FlexPass causes a highly significant reduction of 6.1% in parking consumption (3.40 ± 1.21 days over the 3-month study period), which would render about half of the 380 stacked spaces unnecessary . This is a reduction of value to our university.

Our second contribution is an experiment focused on denser measurement of a price or incentive response curve. We aim to measure demand over a range of prices. Measurement at two prices, as happens in before-after studies and in our RCT yields the minimal two points required to estimate a curve. One would prefer a curve supported by demand measurements over a larger set of prices. A better-supported curve is sometimes obtained without an experiment, such as in time-varying highway tolls [19] or Uber surge pricing [22]. Demand is naturally measured over a range of prices. However our method is an experiment executed only to collect data and transportation does sometimes use experiments when such data is not naturally available.

The experiments are usually exploratory changes of price limited by region or time period. The SFPARK study [42] of our VPP program changes parking prices every 2 weeks in a small region of San Francisco and measures occupancy. Between 1996 and 1999, the San Diego Association of Governments conducted a congestion pricing demonstration project on the I-15. An existing High Occupancy Vehicle (HOV) lane was converted to a High Occupancy Toll (HOT) lane, and evaluations find that by the end of 1999, the HOV lane was much better utilized [50]. The Land Transport Authority in Singapore started a 1-year early morning free transit program in 2013. A before-after comparison shows that about 7% of riders shifted out of the peak commute [27]. In 2014, the city of Berkeley conducted a parking pricing experiment analyzing parking occupancy rates in three neighborhoods. Traveler satisfaction surveys conducted before and after the price changes show that drivers found it easier to find a parking spot [15]. The Bay Area Rapid Transit (BART) offered a 6-month test program in 2017 called BART Perks that provided incentives to riders for traveling during the shoulder hours of the morning peak period. Ten percent of the trial's participants shifted their ride from the peak to shoulder hours [21].

Our second experiment is a repeated second-price auction conducted with 215 subjects over 61 working days. This experiment is the FlexPassPlus study of FHWA's VPP program [52]. The subjects are university employee parking permit holders. Each day, a subject is offered an incentive choice set that includes every incentive between \$0 and \$15 in \$0.25 increments to give up the day's parking. The choice set is made available to every subject, for the 61 working days using our IT system. The system consists of iPhone and Android smartphone apps and a server in the cloud. The choice is provided through the Becker–DeGroot–Marschak (BDM) mechanism [6]. A subject asks for an incentive to sell her parking on campus for the day through the smartphone app. The app then generates a random amount as market price, uniformly distributed, between \$0 and \$15. If the random amount was greater than or equal to the ask, the subject won, and was paid the random number and not permitted to park on campus that day. Subjects knew that an enforcement officer was authorized to issue a \$72 citation to any subject winning the auction and parking on campus. The IT system also collected location data, daily commute mode reports, and weekly parking consumption reports. The bid data is a direct measurement of the parking incentive response curve for our 215 subjects.

The second-price auction has been widely applied in experimental economics to measure consumer willingness to pay (WTP). There are several variants of the second-price auction and we use the Becker–DeGroot–Marschak (BDM) mechanism. The term "second-price auction" was first described academically by Vickrey in 1961 [55]. Vickrey specifies a type of sealed-bid auction, the Vickrey–Clarke–Groves (VCG) mechanism. Bidders submit bids without knowing the bid of the other people. The highest bidder wins, but the price paid is the second-highest bid. In the VCG auction, each bidder maximizes their expected utility by bidding their valuation of the item for sale. The BDM method is a variation of the VCG mechanism [6]. In a BDM auction, the subject formulates a bid, and the bid is compared to a random price determined by a random number generator. If the subject's bid is greater than the price, she pays the random price and receives the item being auctioned. From the subject's perspective, the method is equivalent to a VCG auction against an unknown bidder and thus truth revealing. The BDM method enjoys two major advantages: It is not vulnerable to bidder collusion, and the time cost of participating in a BDM auction is low, especially in repeated auctions.

We then estimate the curve for the entire employee population of the university using a quantile regression. Unlike a before-and-after experiment, our incentive offer is the auction mechanism, which remains fixed throughout the study. Therefore, all variation in the bids made by a subject over the 61-day period is either random noise or due to factors such as the weather, events, changes in schedule, or day of the week which are usually confounding in before-and-after studies. They are measured by the bid variations in ours and are therefore separable from the effect of the incentive. Accordingly, in section 3.4 we are able to present incentive response curves separated by weather and day of the week. We measure the parking incentive response curve for each day during our study period, as shown in figure 1.1. For example, 18.3% of our subjects should relinquish parking for a \$5 incentive on a sunny Monday. This number is 15.8% on a cloudy Friday.

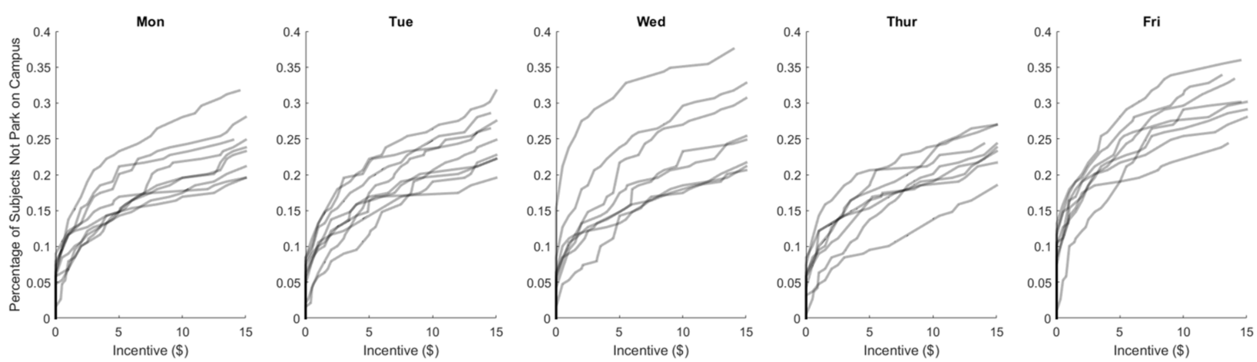


Figure 1.1: Parking incentive response curves for every working day divided by weekdays

Price or incentive response curves are also estimated using discrete choice models supported by stated preference (SP) surveys. These surveys can be designed to elicit preference over a range of prices. Arencibia et al. (2015) conducted an SP survey to estimate freight shipper preferences for different transport modes and estimated a mixed logit model with random taste heterogeneity [4]. The price elasticity is converted from the price coefficient [56], and the demand curve is obtained by estimating the distribution of the WTP. Hössinger et al. (2017) used an SP survey to estimate the response to hypothetical fuel price changes beyond the scope of previous observations. They elicit fuel price elasticities for price increases and find that the situational approach predicts the actual responses to previously observed fuel price changes very well [25]. Ng (2014) utilized a biennial campus-wide transportation and housing survey at UC Berkeley, complemented with an SP survey of 4,188 campus employees, to estimate one of the first incentive response curves for employee parking. They estimate a parking incentive elasticity of 0.97 [39].

Our estimate of incentive elasticity is 0.51, which is significantly different from the survey-based result. Ours is a revealed preference (RP) method because subjects are paid the incentive they ask for when the mechanism permits. Differences between stated and revealed preferences are widely known in the literature [35, 17]. Ghosh (2001) conducted an SP survey before the San Diego I-15 Congestion Pricing Project was implemented and found that Value of Time estimates from SP models were significantly lower than the revealed preference estimates [18]. Park and Ha (2006) analyzed the impacts of the Korea Train Express (KTX) on air traffic demand by conducting an SP survey 8 months prior to the opening of the KTX. The survey-based result shows that only 14% of passengers would prefer to travel by air. In contrast, the actual results revealed that 28% of air passengers preferred to travel by air after the opening of KTX [41]. The differences between stated and revealed preferences pertain specifically to parking elasticity. A meta-analysis compared parking elasticity estimates from 50 published papers, and shows that parking price elasticities based on SP data are smaller than those based on RP data [32]. Parking price elasticity in the SFPark study 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). We have applied the SPA to our experimental field, namely employee parking at UC Berkeley, and been able to densely sample the incentive range up to an upper limit.

The principal downside of our experiments is cost. In the RCT experiment, it is also difficult to keep the control group engaged in the experiment, since they do not receive the cash-out. In the FlexPass study, we spend $50 per control group subject in order to collect the data, and $28 per subject per month in the FlexPassPlus study. Moreover, we place a $15 daily maximum on the bid, leaving the higher ranges of the incentive curve unexplored. Our studies show that the complexity of offering a daily incentive to many subjects over many months can be overcome by modern app technology.

1.1 Research Objective

This dissertation explores experimental methods to estimate the price or incentive response curve, and it focuses on the following research questions:

1. How to evaluate the causal power of a price or incentive strategy? In particular, how much employee parking demand can be reduced by a daily parking cash-out program?

2. How to estimate the price or incentive response curve? In particular, how does the change in incentive influence the employee parking demand?

3. We have collected a rich price or incentive response curve. How does this help in designing daily parking cash-out schemes?

1.2 Dissertation Outline

Two field experiments are conducted to answer our research questions. Chapter 2 describes the first experiment, a daily parking cash-out program executed as a randomized controlled trial and analyzes its effect size. Chapter 3 describes the second experiment, a repeated second-price reverse auction, and the estimation of a parking incentive response curve. Chapter 4 describes a method to divide the parking market into segments based on the auction data, and designs of hypothetical parking cash-out programs optimized for each market segment. Chapter 5 summarizes the key findings from this dissertation, discusses policy implications, and possible future research.

Chapter 2

Exp. 1: Randomized Controlled Trial to Evaluate a Daily Cash-out Program

This chapter describes a randomized controlled trial executed to quantify the unbundling of monthly parking as a means to reduce employee parking at the University of California, Berkeley. Parking demand reductions would make the university more sustainable and free valuable land for education. Employee parking is a benefit provided by the university at reduced rates. Therefore, we consider in this study a monthly parking permit that is price-neutral and unbundled with the potential to reduce parking while enhancing employee welfare. Its causal power is revealed by a randomized controlled trial with a sample of 392 employees.

2.1 Literature Review

Employees purchase a monthly parking permit for a fixed fee, usually with pre-tax dollars. The fee is independent of the number of days parked during the month. All subjects in our trial purchase a monthly permit in exactly the same way, but receive monthly rebates proportional to the number of days not parked. The proportionality is intended to make employees more mindful of parking usage and incentivize its reduction. This new permit studied is called the FlexPass.

According to the Bureau of Transportation Statistics [44], nine out of ten Americans travel to work using personal vehicles. For those who drive, 95% are provided with a parking space free of charge [46]. A number of cities and employers have realized that "free parking" is a key contributor to many negative environmental, social, economic, and aesthetic externalities, and thus have shown increasing interest in more rigorous parking management and pricing [47]. Several studies have demonstrated that charging for parking will lead some travelers to move to other commute options [57, 31, 11]. However, there are practical difficulties in raising employee parking prices. Our experiment validates a daily parking cash-out program, rather than a pricing program. In most employer-owned parking lots, the permit prices remain below market because parking has become an employee entitlement. On our campus, for example, parking price elasticity tends to be quite low. Proulx et al. (2014) developed a parking choice model on the basis of a biennial campus-wide transportation and housing survey at the University of California, Berkeley. They estimated that even if price increases substantially, many travelers are likely to continue to drive and park [43]. Parking incentive is effective in this case, as compared to a substantial rise of the parking prices [20]. A well known parking incentive program is the 1992 California parking cash-out law. This law requires employers that provide subsidized parking to their employees to offer a cash allowance in lieu of the parking space. Employees who choose to give up their parking space are offered a payment that can be used to purchase transit fares or be kept as cash. Shoup evaluated eight employer cash-out programs following the California parking cash-out law and found that, on average, the programs reduced drive-alone trips from 76% to 63% of total commute trips [45]. Parking cash-out is successful because it applies a value to a commodity that is often perceived as free, and it encourages employees to make travel decisions that maximize their individual welfare. Compared to a monthly subsidy, daily cash-out provides both incentives and flexibility and has been found more likely to shift commuter mode choice [31]. However, daily parking cash-out programs are rarely explored. A daily parking cash-out program, the VPP PayGo Flex-Pass, was tested in Minneapolis, Minnesota, in 2010 and 2011 [31]. It provided a rebate of $7 on days where parking was not used. Thirty-one subjects were enrolled in the study for five months. The PayGo Flex-Pass led to a decline in driving days from 78.5% to 56.5%. All the parking data was collected through an online survey system. In part due to technical issues with this data collection system, only a small amount of before and after data was able to be obtained for comparison. Also, due to limited sample size, the effect is not statistically significant. The experiment described in this chapter tests another daily parking cash-out program, the FlexPass, through a randomized controlled trial with 392 subjects during the spring 2015 semester, February 1, 2015 to April 30, 2015.

In the transportation pricing literature, *ex post* evaluations are often done by before-and-after experiments (e.g., Minnesota Pay-as-You-Drive [1], California Parking Cash-out [45] and Minneapolis PayGo Flex-Pass [31]). In a before-after experiment, the price or incentive is changed and the corresponding consumption is measured before prices are changed again. The before-and-after experiment produces a temporally or spatially distributed sequence of price changes with corresponding consumption data. The sequences are then used to evaluate the new pricing strategy. Evaluation is straightforward if one can assume that the measured changes in consumption are caused by the changes in prices. However, many of the experimental studies we have cited recognize reality to be more complex and model to control for confounding factors (for example, weather or large events) that are concomitant with the price changes and also affect consumption. A randomized controlled trial (RCT) is a type of scientific experiment which aims to reduce bias when testing a new treatment.

In most RCTs, subjects are divided into two groups, one receiving a treatment and one receiving a placebo, at random. The researcher does not control who is put in which group. The RCT is considered a gold standard of evidence in medical research. As of 2004, more than 150,000 RCTs were conducted in the medical field [49]. The first published RCT in medicine appeared in the 1948 [37, 7]. Later, randomized experiments were used in psychology, education, and agriculture [48, 14]. The disadvantages of an RCT are the cost and study execution. In terms of testing the effect of a new daily parking cash-out program, one difficulty is to keep the control group unexposed to the new scheme. We needed to introduce an IT system to record subjects' parking consumptions. After that, different drivers could receive different incentives based on their group assignment and parking consumptions. The other issue is to prevent the control group from dropping out. As the control group do not receive any incentives during the experiment, they become inclined to stop sending their travel information.

The chapter begins with a description of the experimental design in section 2.2, followed by a description of the subjects' socioeconomic characteristics. We then discuss the data collected in the trial and demonstrate how we correct underreporting and dropout biases in section 2.3. Underreporting is corrected by processing data from email surveys. Dropout biases are captured by a sample selection model. Finally, the effect size of FlexPass is estimated.

2.2 Experimental Design

The FlexPass study is a randomized controlled trial [9] with the FlexPass as the treatment. Most UC Berkeley employees who purchase an annual parking permit elect to pay through pre-tax dollars. All permits are pre-paid, and the treatment in this study refunds a portion of the pre-paid amount to the FlexPass holder for each day not parked. The treatment is intended to make the employee mindful of parking usage and incentivize its reduction.

The study was advertised to all permit holders and aimed to recruit 400 subjects from 2,958 parking permit holders, in other words, approximately 15% of the population. The recruitment emails are attached in appendix B. By completing a sign-up process (see appendix D) before an advertised recruitment deadline, 392 permit holders became the study subjects. Thereafter, the subjects were randomly assigned to a treatment or control group, see appendix E. The study then attempted to measure the number of working days that each subject parked over a three-month period (February, March, and April) within the spring semester 2015. Any difference between the treatment and control groups as measured by the average number of days parked per subject is hypothesized to have been caused by the treatment by virtue of the random assignment.

Parking usage was measured by requiring each subject to use the FlexPass app. All subjects were required to be either iPhone or Android users. Figure 2.1 illustrates the main app screens. The subject could tap the green box on the main screen to indicate whether she intended to park or not on each day. Parking could also be declared in advance using a calendar screen. The green box toggles when tapped between “Parked on Campus” and “I will not park on campus today.” A subject can change her parking decisions for a certain day until 12 noon of that day. Thereafter the statement in the green box is assumed to be the subject’s final parking decision for the day. Treatment group subjects indicating that they would not park for the day were credited a rebate amount and could be cited by enforcement officers if observed parked. The green box was set by default to “Parked on Campus” because subjects pre-paid for the right to park. Subjects toggling the default to “I will not park ...” were prompted to report whether they were not coming to campus or were doing so by some other mode as shown on the second screen.

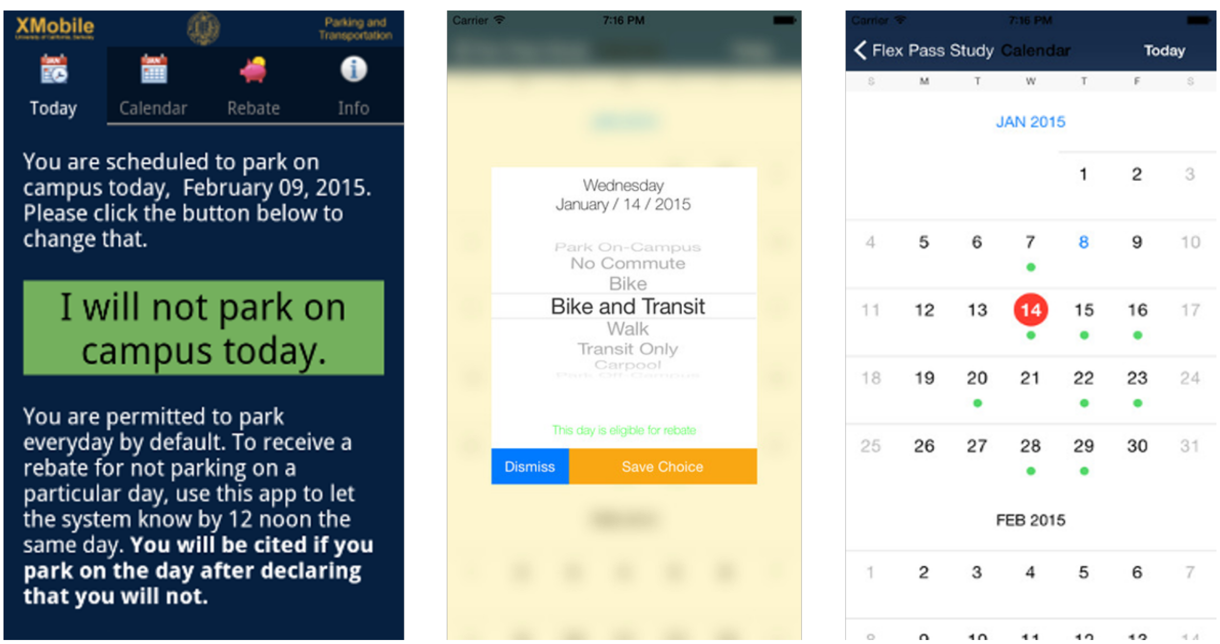


Figure 2.1: FlexPass smartphone app interface. From left to right, (a) Main Screen, (b)Mode Reporting, (c) Calendar

Control group subjects received neither rebate nor citation. Their lack of incentive to report and the default setting of “Parked on Campus” resulted in an underreporting bias discussed and corrected in section 2.3. Subjects with no app activity during a week were prompted to report at the end of the week. The email included a web link to report the number of days parked or not during the week.

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 also compensated the same amount. Thus, most subjects received $50 in Amazon gift cards in two installments.

Subjects assigned to the treatment group were required to exchange their usual permit hang-tags for new FlexPass hangtags by meeting with UC Berkeley Parking and Transportation (P&T) Department personnel prior to February 1, 2015. Control group subjects were not required to do this. Some treatment group subjects did not make the exchange. Our analysis includes statistical corrections to correct the resulting bias (see section 2.3).

The enforcement function was executed by UC Berkeley's P&T Enforcement Officers. The study team emailed to the enforcement officers a list of FlexPass permit numbers not parked at 12 PM each day. Any FlexPass permit with a number on the list could be cited.

This study treatment targeted the current annual Central Campus **C** Permit and Faculty/Staff **F** Permit holders, who 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 by the permit type. **C** permits are available only to faculty and senior staff, **F** permits to other staff. During the study, the pre-pay price for an **F** permit was $95 per month and $131 per month for **C** permit. Subjects were recruited from the 2,958 employees who had already purchased a **C** or **F** permit for the entire 2015 spring semester.

Rebates to subjects in the treatment group were based on their permit types and the number of working days (Mon. to Fri.) they would park on campus in a given month. Rebate amounts were calculated as equation 2.1 below.

$$T = \max\{\Theta - D\delta, 0\} \tag{2.1}$$

where D is the number of working days a certain subject parks on campus in a certain month and T is the total rebates for the month. The maximum monthly rebate is $\$\Theta$ (Θ=95 for **F** permit holders and 131 for **C** permit holders). For each day parked on campus, a subject was charged $\$\delta$ (δ =6 for **F** permit holder or 8 for **C** permit) until the entire prepaid amount for the month had been used up. For example, an **F** permit holder parking 12 workdays on campus (approximately three workdays per week) received a rebate of $23. Detailed description of the rebate calculation and a table of all possible rebate values can be found in appendix C.

Sample Characteristics

Among the 2,958 **C** and **F** permit holders at UC Berkeley we reached through emails and postcards, 392 respondents finished the sign-up process to become subjects. They were equally divided into the treatment group and the control group. Table 2.1 summarizes their demographic and socioeconomic information. All the information was collected through the entry survey; see appendix D. UC Berkeley staff make up the bulk of the sample. Females account for 71% of staff subjects and 57% of faculty. Most subjects are over 25 and under 65 years old. Thirty percent of the subjects have at least one bike, while 35 % have a Clipper card, which is a reloadable contactless card used for electronic transit fare payment in the San Francisco Bay Area. These provide them potential alternative commute modes when not parking on campus. Seventy-seven percent of the subjects felt interested in the potential rebates. The remaining 33% would have liked to support the research but were not interested in the rebates. Seventy-one people wrote reasons for not being interested in the rebates. Typical reasons included "Must park each workday," "I need to get to my children from time to time," and "No alternatives for me other than driving my car." Subjects were asked about their weekday commute modes in the week prior to the sign-up. Seventy-six percent of subjects came to campus all five weekdays. Seventy-nine percent of subjects drove alone and parked on campus more than four working days.

2.3 Causal Analysis of the FlexPass Study

We infer the treatment effect of the FlexPass using a box model as shown in Figure 2.2(a). From a box of 2,958 **C** and **F** permit holders, 392 samples were drawn and assigned into treatment and control groups randomly. The group assignment of a subject i is denoted as T_i. Y_i^T, and Y_i^C denote the potential outcomes given FlexPass treatment, $T_i = 1$, and non-treatment, $T_i = 0$, respectively. For each subject, one or other of the potential outcomes in counterfactual. The observed outcome is $Y_i = T_i Y_i^T + (1 - T_i) Y_i^C$. Y_i is a 64-dimension binary vector, where Y_{ij} is subject i's parking choice on day j. Y_{ij} equals 1 if he or she did not park on campus on day j and 0 if he or she did, Subjects' social economic characteristics, denoted as X_i on the ticket, were measured in the entry survey. The total number of days parked on campus by subject i during the study is then $y_i = \sum_j Y_{ij}$.

If all the data Y_{ij} were observed, then the statistic $E(y_i|T_i = 1) - E(y_i|T_i = 0)$ would be an unbiased estimator of the treatment effect. However, some treatment group subjects dropped out after recruitment, and not all of the Y_{ij} were observed; in other words, we have missing reports. Moreover, dropouts and missing reports are correlated with the assignment of subjects into treatment and control. This would render the naive estimator biased. This section describes the methods we use to correct these two biases. Subsection 3.1 illuminates the biases in the data, and reveals the missing report mechanism. The next subsection is about the method used to correct the missing report bias. Subsection 3.3 does the same for

Table 2.1: Sample Descriptive Statistics

	Treatment	**Control**	**Enrolled**
UC Berkeley employment status	(%)	(%)	(%)
FACULTY	22.4	19.1	20.8
STAFF	77.6	80.9	79.2
Age Group			
EIGHT-TEEN TO TWENTY-FOUR	2.5	1.6	2.0
TWENTY-FIVE TO THIRTY-FOUR	24.4	26.1	25.2
THIRTY-FIVE TO FORTY-FOUR	30.5	25.6	28.0
FORTY-FIVE TO FIFTY-FOUR	24.9	31.5	28.2
FIFTY-FIVE TO SIXTY-FOUR	15.2	13.3	14.3
SIXTY-FIVE AND OLDER	2.5	2.0	2.3
Gender			
FEMALE	65.6	65.0	65.3
MALE	34.4	35.0	34.7
Has bike			
FALSE	68.4	71.6	70.0
TRUE	31.6	28.4	30.0
Has Clipper card			
FALSE	66.3	64.2	65.3
TRUE	33.7	35.8	34.7
Rank mobile app			
1st	58.5	50.6	54.5
2nd	28.7	29.3	29.0
3rd	12.9	20.1	16.5
Rebate interested			
FALSE	21.4	23.0	22.2
TRUE	78.6	77.0	77.8
Number of days drives alone			
5	66.8	61.7	64.3
4	13.8	16.8	15.3
3	8.2	8.7	8.4
2	6.1	5.6	5.9
1	2.0	2.6	2.3
0	3.1	4.6	3.8
Number of participants			
	196	196	392

the dropout bias. The missing reports are imputed by email surveys, while dropout bias is compensated for using a selection model. The selection model reveals the causal treatment effect.

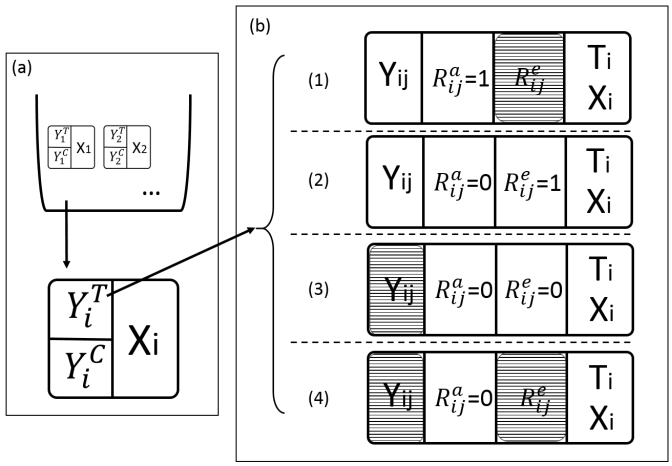
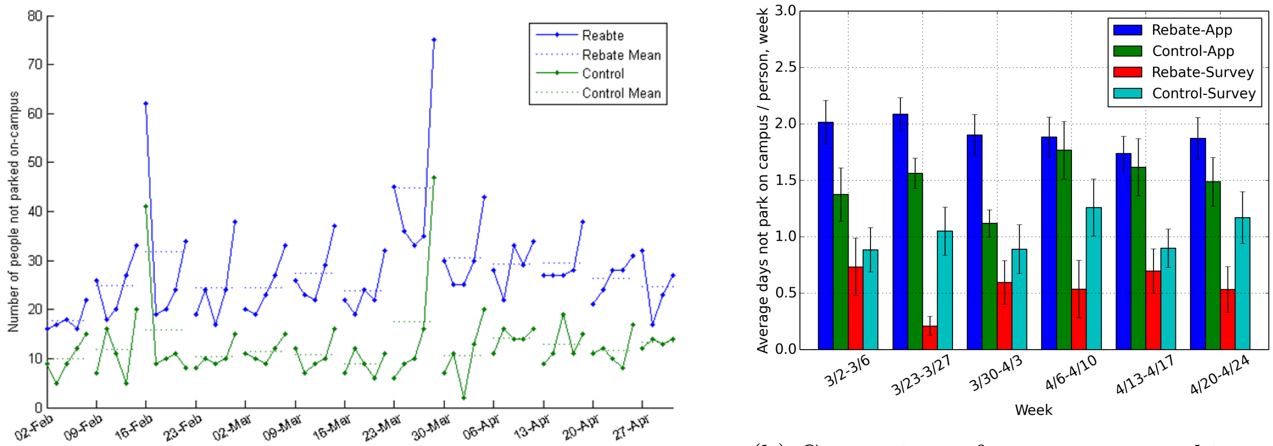


Figure 2.2: Box model for causal analysis

Dropouts, Missing Report Mechanism, and Data Descriptions

The app-reported parking demand reductions are shown in Figure 2.3a. The blue line which represents the treatment group is always above the green line which represents the control group. This may be an indicator for significant treatment effect at the first sight. However, this comparison relies on a strong assumption that when people did not report anything through the app on certain days, they were considered as "Park on Campus". In fact, the exit survey after the study showed that sometimes subjects forgot to use the app when they did not use campus parking. Especially for subjects in the control group, there were no incentives for them to report daily commute modes. In fact, during the entire study period, 74 subjects in the control group reported nothing through our app. Even with subjects who reported some parking activities, they still may have under reported the number of not-park-on-campus days, which may have led to an overestimation of the treatment effect. Therefore, instead of app-response Y_{ij}, we additionally define, for each occasion j, an indicate R^a_{ij}, which equals 1 if the subject i reported day j's parking behavior through smartphone app and 0 if the subject i did not use the app on day j. We then partition Y_i into two sub-vectors such that Y^o_i is the vector containing those Y_{ij} for which $R^a_{ij} = 1$ and Y^m_i contains the remaining components. Y^m_i refers to missing reports. To further understand the missing report process, we sent commute mode surveys in the six weeks during the study to those who had not used their smartphone app for a week prior to the survey. The survey asked subjects about their daily commute choices in the past week. The average response rate for the email survey was

62.2%. Hence for each occasion j, another indicator is defined as R^e_{ij}, which equals 1 if the subject i reported day j's parking behavior through email and 0 otherwise.



(a) Daily on-campus parking demand reduction for rebate and control groups

(b) Comparison of non campus parking days between app reports and email responses

Figure 2.3: Measurements of parking behavior

From the email survey, a hypothesis test of the missing report mechanism was conducted among three alternates: Missing Completely at Random (MCAR), Missing at Random (MAR), and Missing Not at Random (MNAR) [34]. The three mechanisms differ from each other based on the dependencies between missingness and observed and unobserved data. Missing Completely at Random refers to the missingness independent of both observed and unobserved data; MAR refers to missingness independent of unobserved data; MNAR refers to missingness independent of neither observed or unobserved data. The missingness process for MCAR and MAR are ignorable such that we can ignore formulating the missingness process when we are inferring the treatment effect. Otherwise, if the MNAR holds we should model the missingness process before conducting causal analysis. In the FlexPass study, we consider the missingness app reports to be Missing Not at Random (MNAR). A possible evidence is that subjects were aware that the default choice on the app is "Park on Campus." Thus, they did not report via the app when they did park on campus. We compare the outcomes from follow-up emails with app reports shown in Figure 2.3b. It can be observed that the email responses of non-campus parking days are generally lower than the app reports. In those six weeks when surveys were sent, the app reports resulted, on average, 1.92 non-campus parking days per week among the treatment group, while this number is 0.57 for email responses. Through a two-sample t-test, the null hypothesis of MAR leads to a p-value of 0.002, which rejects MAR and also MCAR. The missing report mechanism is regarded as MNAR. The missing reports will be estimated from the email responds.

To sum up, in our study, respond vector Y_i is measured by both app and follow-up email. All possible outcomes for Y_{ij} are then illustrated in Figure 2.2(b), where the shaded region means not observable. In situation (1), the subject i report day j's parking choice through the app, where Y_{ij} is observed and no email will be sent. In situation (2), the subject i didn't use the app on day j and an email will be sent to i. The subject answered the email and thus Y_{ij} is observed. In situation(3), Y_{ij} is not observed as the subject i didn't answer the email. Situation(4) may happen when the subject i was assigned to the treatment group but did not change her parking permit to the FlexPass permit. In this case, she would neither report in the app nor receive any email. Noticeably, part of Y_i^m is measured in situation (2). If Y_i only contains Y_{ij} of situation (3) and (4), the subject i is regarded as a "Dropout subject". Otherwise, complete data Y_i will be recovered from Y_{ij} observed in situation (1) and (2).

Recover Missing Reports

To infer treatment effect, $E[Y_{ij}|T]$ needs to be estimated, which can be calculated by conditioning on ${R^a}_{ij}$:

$$E[Y_{ij}|T] = E[Y_{ij}|T, {R^a}_{ij} = 1]P({R^a}_{ij} = 1|T) + E[Y_{ij}|T, {R^a}_{ij} = 0]P({R^a}_{ij} = 0|T)$$

We assume days and individuals are independent and identically distributed (i.i.d.). Under i.i.d., $E[Y_{ij}|T, {R^a}_{ij} = 1]$ can be estimated directly by averaging over app reports. $P({R^a}_{ij} = 1|T)$ and $P({R^a}_{ij} = 0|T)$ can be estimated by counting the frequency of app usage. $E[Y_{ij}|T, {R^a}_{ij} = 0]$ is the missing part. If all the subjects truthfully report their not-park-on-campus days through the app, this term is 0. However, section 2.3 shows that missing reports exist and $E[Y_{ij}|T, {R^a}_{ij} = 0]$ needs to be evaluated. Conditioning on the email responds ${R^e}_{ij}$:

$$\begin{aligned} E[Y_{ij}|T, {R^a}_{ij} = 0] \quad = \quad & E[Y_{ij}|T, {R^a}_{ij} = 0, {R^e}_{ij} = 1]P({R^e}_{ij} = 1|T, {R^a}_{ij} = 0) + \\ & E[Y_{ij}|T, {R^a}_{ij} = 0, {R^e}_{ij} = 0]P({R^e}_{ij} = 0|T, {R^a}_{ij} = 0) \end{aligned}$$

The email survey was conducted after the end of each week; survey responses do not affect rebate calculation. Therefore, we assume parking behavior is independent of email survey reporting behavior. Under this assumption of Y_{ij} being independent of ${R^e}_{ij}$, $E[Y_{ij}|T, {R^a}_{ij} = 0, {R^e}_{ij} = 1]$ equals $E[Y_{ij}|T, {R^a}_{ij} = 0, {R^e}_{ij} = 0]$, where $E[Y_{ij}|T, {R^a}_{ij} = 0, {R^e}_{ij} = 1]$ can be estimated directly form the email survey responses. The recovered parking response matrix $\hat{\mathbf{Y}}$ is then computed through the following formula:

$$\widehat{Y_{ij}} = \begin{cases} \frac{\sum_j Y_{ij}(1-{R^a}_{ij}){R^e}_{ij}}{\sum_j (1-{R^a}_{ij}){R^e}_{ij}}, & \text{if } {R^a}_{ij} = {R^e}_{ij} = 0 \\ Y_{ij}, & \text{otherwise.} \end{cases}$$

Compensate Differential Dropout Bias

For valid subjects, y_i can be calculated from the recovered parking response matrix $\hat{\mathbf{Y}}$, such that $y_i = \sum_{j=1}^{N} \widehat{Y}_{ij}$. For dropout subjects, i.e., subjects in the treatment group who did not pick up the FlexPass hang-tag and people in the control group who did not report any parking choice during the study, their y_i's are unobservable. We denote a dropout indicator R_i^d, where $R_i^d = 0$ if the subject i dropped out and 0 otherwise. The naive estimator using observed outcomes, $E(y|T = 1, R^d = 1) - E(y|T = 0, R^d = 1)$, will be biased because of the existence of non-random dropout as a confounder. Existence of non-random dropout in randomized controlled trials are not rare (e.g., experiments of new drug impact). Often, the subjects can decide themselves, whether they accept the treatment, which is not under researchers' control. This problem is usually referred to as a sample selection or self-selection problem [23]. Additional information is required to estimate the causal effect under this scenario. Popular choices include pseudo-randomization, instruments, and the information about the functional form of the selection process. As the reason for dropout was explicitly known in our study, sample selection model was employed.

We first consider a homogeneous treatment effect δ which does not vary over individuals. The sample selection model with differential consists of the following structural process:

$$\begin{aligned} y_i^* &= \beta^{O\prime} X_i{}^O + \delta T_i + \varepsilon_i{}^O \\ R^{d*}{}_i &= [T_i \beta_T{}^S + (1 - T_i)\beta_C{}^S]' Z_i{}^S + \varepsilon_i{}^S \end{aligned}$$

where R_i^{d*} is the realization of the latent value of the selection "tendency" for the subject i, and y_i^* is the latent outcome of total non-campus parking days during the study. $X_i{}^O$ is a explanatory variables including some background characteristics of enrolled subjects. $Z_i{}^S$ is explanatory variables for the selection equation. Identification requires $X_i{}^O$ to be at most a strict subset of $Z_i{}^S$ (there should be at least one variable in $Z_i{}^S$ that is not also in $X_i{}^O$). As dropouts happened in both groups due to different reasons, a differential dropout process is modeled. $\beta_T{}^S$ and $\beta_C{}^S$ represents parameters describing distinct dropout processes for treatment and control group respectively. We observe:

$$\begin{aligned} R_i^d &= \begin{cases} 0, & \text{if } R_i^{d*} < 0 \\ 1, & \text{otherwise} \end{cases} \\ y_i &= \begin{cases} \text{unknown}, & \text{if } R_i^d = 0 \\ y_i^*, & \text{otherwise} \end{cases} \end{aligned}$$

That is, we observe the parking response only if the latent selection R_i^{d*} is positive, which means the subject i did not dropout. The observed dependence between non-campus parking frequency y_i and treatment T_i can now be written as:

$$E[y|T = T_i, R^d = 1, X^O = X^O{}_i] = \beta^{O\prime} X_i{}^O + \delta T_i + E[\varepsilon_i{}^O | \varepsilon_i{}^S \geqslant -[T_i \beta_T{}^S + (1 - T_i)\beta_C{}^S]' Z_i{}^S] \tag{2.2}$$

The third term in equation 2.2 illustrates why the naive estimator using observed data gives in general a biased result. $E[{\varepsilon_i}^O|{\varepsilon_i}^S \geqslant -[T_i{\beta_T}^S + (1-T_i){\beta_C}^S]'{Z_i}^S] \neq 0$ unless ${\varepsilon_i}^S$ and ${\varepsilon_i}^O$ are independent; in other words, the dropout process is completely random. Parameters can be estimated effectively through a maximal likelihood method by assuming that the error terms follow a bivariate normal distribution:

$$\begin{pmatrix} \varepsilon^S \\ \varepsilon^O \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & \sigma^2 \end{bmatrix}\right)$$

where ρ describes the relationship between observed non-campus parking frequency and dropout process. $\rho > 0$ indicates a "positive selection," where subjects who remained in the study are those who forwent campus parking more often. $\rho < 0$ indicates a "negative selection," where subjects who forwent parking more often dropped out. $\rho = 0$ indicates that subjects' parking behavior is independent of the dropout process.

The probit results for selection process in Table 2.2 offer clear insights into how social economic features influence the probability of dropout in treatment and control groups. Subjects who stay valid in the treatment group are those who went to the P&T office in person and changed to the new hang-tag, which can be viewed as expending an extra time cost. Table 2.2 column (1) suggests that owning a Clipper card decreases the odds of dropout in the treatment group; being interested in rebates increased the probability of staying valid. Indeed, the selection process implied that there may exist "positive selection" that people with potential alternative commute modes and with willingness to collect the rebate tend to remain active in the treatment group. Control group subjects those who never used the app nor replied to the email survey were considered as dropped out. Table 2.2 column (2) describes the control group dropout. We found that subjects who prefer not to receive information through the smartphone app tend to drop out when assigned to the control group.

The regression result for measurement equation in the sample selection model is provided in Table 2.3. Two ordinary least squares (OLS) regressions were also conducted directly based on 306 observed parking responses as baseline. All five models gave similar estimates for the effect of being UC Berkeley full-time staff members. Staff significantly parked about four days more than faculty. This may be caused by their more restricted working schedules. The regression also showed that subjects owning bikes parked on campus less often. In models (1) and (3), the homogeneous treatment effect was estimated. The selection model suggested a highly significant average treatment effect of 3.298 fewer on-campus parking days per subject during three months. The correlation between selection and observation process ρ was highly significantly positive. We interpret this as an indicator for"positive selection." The OLS estimated a larger and more significant treatment effect, which, however, is biased.

We further consider the existence of heterogeneous treatment effect, where the FlexPass' treatment effect varied among different types of individuals. This is captured by an interaction term in models (2), (4), and (5). In the sample selection model with the interaction term of "Rebate interested", model (4), there is no significant treatment effect for people who had reported as not interested in the rebate when they signed up. According to the entry survey, before the study, non-rebate-interested subjects parked on campus for 4.6±1.1 days per week, while rebate-interested subjects parked on campus 4.1± 1.3 days per week. Non-rebate-interested subjects generally have a hard demand for driving and parking on campus, with small price elasticities. The size of treatment effect on rebate-interested subjects was 4.541 days with standard error 1.359 (the covariance between the coefficients of interaction term and treatment was -7.219). In the sample selection model with the interaction term of 'Has BusPass', model (5), there is a barely significant treatment effect for subjects who do not own discounted bus passes. The size of treatment effect on having-bus-pass subjects was 11.243 days with a standard error 3.161 (the covariance between the coefficients of interaction term and treatment was -1.531).

As mentioned before, as compared to the OLS, the sample selection model produces conservative estimates of the treatment effect. Although our estimation of treatment effect may still be biased, it is in the safe direction. Therefore we conclude that FlexPass did change subjects' parking behavior. On the population level, the treatment effect of FlexPass was 3.298 days per subjects, which is a 0.2-day reduction per week, a 6.1% reduction in parking demand. On our campus, there are 2,080 regular parking spaces reserved for the 2,958 permit holders. The campus operates another 380 stacked parking spaces in order to meet excess demand. With the 6.1% reduction generated by the daily parking cash-out, more than half of the stacked parking space could be removed. That removal can improve service level and save maintenance expenses. For subjects reported interested in the incentives, which is 77.8% of the population, the treatment effect of FlexPass was 4.541 days per subjects, which is a 0.35-day reduction per week, a 8.1% demand reduction. For subjects having discounted bus passes, which is 13.0% of the population, the treatment effect of FlexPass was 11.24 days per subjects, which is a 0.88-day reduction per week, a 20.6% demand reduction. These reductions were achieved with an average rebate of nearly $27 per subject over a three-month period. The study suggests that a daily parking cash-out program, which unbundles the monthly parking permit with moderate incentive payments, can reduce employee parking.

2.4 Conclusion

Employee parking is a benefit provided by the university at below-market rates. Large employers such as the University of California, Berkeley, nevertheless need to increase greener travel for economic and sustainability goals. To this end, the FlexPass study has explored reducing the number of employees who drive alone and park by testing a pay back scheme that unbundles the monthly parking permit. UC Berkeley employees usually pre-pay for monthly parking by buying a permit. The FlexPass treatment rebates some or all of this amount in proportion to the number of days not parked.

Table 2.2: Casual Inference Results from Sample Selection Model: Selection Equation

	Dependent variable:	
	TreatmentValid	ControlValid
	(1)	(2)
I am of age group *senior*	0.116	-0.666^{**}
	(0.314)	(0.297)
My gender is male	0.307	0.027
	(0.265)	(0.222)
I have a bike	0.420	0.241
	(0.270)	(0.236)
I have a Clipper card	0.541^{**}	0.030
	(0.257)	(0.218)
I am Berkeley staff	0.665^{**}	0.251
	(0.271)	(0.270)
Days I did not commute	0.159^{*}	0.204^{**}
	(0.089)	(0.092)
Mobile app rank	0.084	-0.191^{*}
	(0.132)	(0.114)
I am interested in rebates	$0.793^{\dagger}$	-0.340
	(0.251)	(0.262)
Constant	-0.977^{**}	0.674
	(0.449)	(0.428)
Observations	196	196
Log likelihood	-83.604	-101.530
Akaike Inf. Crit.	185.208	221.061
Note:		*p<0.1; **p<0.05; †p<0.01

Table 2.3: Casual Inference Results from Sample Selection Model: Observation Equation

	Dependent variable:				
	noPark				
	OLS		*selection*		
	(1)	(2)	(3)	(4)	(5)
Rebate	3.836†	−2.520	3.298†	−1.297	2.082
	(1.195)	(2.633)	(1.214)	(2.669)	(1.280)
I am Berkeley staff	−4.037†	−3.642**	−4.434†	−4.283†	−4.122†
	(1.462)	(1.440)	(1.478)	(1.460)	(1.462)
I have a BusPass	4.896†	0.080	4.665†	4.491†	−0.051
	(1.750)	(2.475)	(1.734)	(1.719)	(2.438)
I have a bike	2.306*	2.637**	1.793	2.036	1.974
	(1.303)	(1.283)	(1.326)	(1.314)	(1.309)
I am interested in rebates	2.096	−0.825	1.618	−0.881	1.518
	(1.533)	(1.982)	(1.546)	(2.003)	(1.526)
Rebate: I have a BusPass		8.772**			9.162†
		(3.426)			(3.379)
Rebate: I am interested in rebates		6.441**		5.838*	
		(2.961)		(3.027)	
Constant	7.852†	10.250†	10.518†	11.942†	10.831†
	(1.953)	(2.118)	(2.121)	(2.258)	(2.109)
Observations	306	306	392	392	392
R^2	0.111	0.149			
Adjusted R^2	0.094	0.126			
Log likelihood			-1,337.746	-1,335.918	-1,334.127
ρ			0.423†	0.369†	0.407†
Note:					*p<0.1; **p<0.05; †p<0.01

We designed the FlexPass study as a randomized controlled trial to learn if daily rebates can reduce employee parking. The trial measures the number of days parked or not parked by requiring subjects to report parking each day using an app. The same information was solicited in weekly emails from subjects not using the app. The causal effect of the FlexPass is quantified by estimating the average number of days parked per subject in the treatment and control groups.

The causal analysis of the treatment effect applies the longitudinal parking usage data produced by the app using the box model. Two biases were estimated using the email reports and the selection model. Underreporting in the app is quantified as Missing Not at Random. Dropout biases are estimated by a sample selection model. We present both the OLS and selection model. The selection model has a conservative result. We estimate the FlexPass causes a highly significant reduction of 6.1% in parking consumption (3.40 ± 1.21 days over the three-month study period). Seventy-seven percent of the subjects reporting interest in the incentives a priori show a greater and more significant demand reduction. The FlexPass caused an on-campus parking demand reduction of 4.54 days per subject in this subpopulation, which is a 0.35-day reduction per week, an 8.1% demand reduction. Thirteen percent of the subjects own discounted bus passes, which save over 75% regular ticket price. This subpopulation shows a further demand reduction of 11.24 days during the three months. It is a 0.88-day, or 20.6%, reduction per week.

These reductions required a total rebate of $4256 to the 158 valid subjects in the treatment group. Each subject received $26.94 on average over the entire study period. The highest rebate for an individual is $285 with most rebates being under $20. We find that unbundling a monthly employee parking permit reduces parking by making employees mindful of daily parking usage.

Chapter 3

Exp. 2: Second-Price Auction to Measure the Incentive-Response Curve

The FlexPassPlus experiment described in this chapter explores a new method to measure a parking incentive response curve. The University of California, Berkeley, with 23,962 employees is the largest employer in the eastern half of the San Francisco Bay Area and has a problem with employee parking. UC Berkeley priced campus parking permits for faculty and staff between $95 and $131 per month in the year 2015. The university offers 2,080 regular parking spaces reserved for the 2,958 permit holders. The campus operates another 380 stacked parking spaces in order to meet excess demand. Field observations have found that occupancies are above 85% in most parking lots for much of the workday [39]. The university needs to understand the elasticity of parking demand to prices or incentives to better control its consumption. Hence, we use our method to measure the price or incentive response curve of the permit holder population. The method is a repeated second-price reverse auction. It is a reverse auction because we conduct a daily parking cash-out. Subjects ask each day for the amount they want to receive to relinquish the privilege to park on university property. The auction is repeated because each subject is invited to play each day for 61 working days. We use the Becker-DeGroot-Marschak (BDM) mechanism. A subject can ask for $0 to $15 with $0.25 increments to sell her parking on campus for the day. After the subject submits the ask, we generate a random amount as market price, uniformly distributed, between $0 and $15. If the random amount is greater than or equal to the ask, the subject wins and the ask is accepted at the random number. We will credit that random amount to the subject's account, and the subject will not be able to use 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, she is allowed to park on campus. Violations are enforced, and the enforcement officer will issue a $72 citation if the subject wins the auction but still parks her car on campus. Our method is a revealed preference method, as the subject chooses her commute mode and places the ask in real life, instead of a hypothetical environment. In theory, our method is truth revealing, as the subject maximizes her expected utility by bidding her willingness to accept(WTA) to forgo parking. We prove this in section 3.2. Therefore, we can measure the corresponding demand changes as incentive varies between \$0 to \$15 with \$0.25 increments. We explain this in section 3.3. Unlike a before-and-after experiment, our incentive offer is the auction mechanism which remains fixed throughout the study. Therefore, theoretically, all variation in the bids made by a subject over the 61 day period is either random noise or due to factors such as the weather, events, changes in schedule, days of the week, etc., factors that are usually confounding in before-and-after studies. We show that the effect of incentive is separable in section 3.4.

3.1 Literature Review

The second-price auction has been widely applied in experimental economics to measure consumers' willingness to pay (WTP). There are several variants of the second-price auction. By comparing their pros and cons, we use the BDM mechanism in our experiment. The term second-price auction was first described academically by Vickery in 1961 [55]. Vickery specifies a type of sealed-bid auction. Bidders submit bids without knowing the bid of the other people. The highest bidder wins but the price paid is the second-highest bid. It later became called the Vickrey–Clarke–Groves (VCG) mechanism. In the VCG auction each bidder maximizes their expected utility by bidding their valuation of the item for sale. Hoffman (1993) illustrates the use of laboratory experimental auctions in revealing WTP for new products [24]. Alfnes and Rickertsen (2003) ran simultaneous second-price auctions to elicit the complete distribution of WTP differences among Irish, Norwegian, and U.S. beef [2]. The BDM method is a variation of Vickery's original sealed bid second-price auction [6]. In one common set up of the BDM method, the subject formulates a bid. The bid is compared to a random price determined by a random number generator. If the subject's bid is greater than the price, she pays the random price and receives the item being auctioned. From the subject's perspective, the method is equivalent to a Vickrey auction against an unknown bidder and thus truth revealing. One of the advantages of the BDM method is that it is not vulnerable to bidder collusion. Cunningham (2003) applies the BDM method to measure the impact of information on WTP [12]. Chib (2009) has studied which brain region determines the purchasing decisions among different categories of items [10]. The subjects' value for each item was measured using a BDM auction. Another advantage of the BDM method in field experiments is that subjects can see the auction result directly after they place the bid. As compared to a VCG auction, where the auction result is announced after all subjects submit a bid, the time-cost of participating in the BDM auction is low, especially in repeated auctions. One disadvantage of the BDM auction is that the auction bidding processes do not naturally mimic the consumer decision-making of choosing between alternatives. The multiple price list (MPL) is designed to resolve this problem [3]. The MPL confronts the subject with an array of ordered prices in a table, one per row, and asks the subject to indicate “yes” or “no” for each price. The experimenter then selects one row at random, and the subject’s choice is implemented. The main advantage of this format is that it is relatively transparent to subjects and provides simple incentives for truthful revelation. The main disadvantages are that it could be susceptible to framing effects and only elicits interval responses. In our experiment, to measure the WTA from $0 to $15 with $0.25 increments requires that the subject completes 60 binary choices every day for three months. This tremendous time cost may result in significant drop-out. Therefore we use the BDM mechanism in our experiment. In section 3.3 we demonstrate that the aggregate number of bids per day shows no trend in the 61-day period, meaning that the study sustained subject enthusiasm. In our repeated auction, the random daily incentives were independent of each other. However, it is reported in the literature as the gambler’s fallacy that people tend to believe that results are correlated when facing repeated independent random trials. For example, if the random incentives are all less than $2 in the previous 10 days, the subject may believe the next random incentive should be high. This may bias our WTA measurements. List and Shogren (1999) have examined panel data on bidding behavior over 40 second-price auction markets with repeated trials. The results suggest that the posted price in the previous auction influences the behavior of the median naive bidder [33]. But it does not affect the behavior of the experienced bidder or the bidder for familiar goods. For the permit holder population, we consider that parking is a familiar good. In section 3.3, we demonstrate that our subjects understand the auction rule and bid rationally. We borrow the method of second-price auction from the economics literature and apply it to measure permit holders’ parking incentive response curve.

In the transportation pricing literature, the estimation of the parking price/incentive response curve has arisen within several different research traditions. To estimate a parking price/incentive response curve, we need a data set of price changes and corresponding parking demands. There are three ways to collect this data: through a revealed preference (RP) survey, stated preference (SP) survey, and before-and-after experiment. In terms of estimation method, most studies use the constant elasticity model as a first-order approximation of the parking price-response curve and estimate the parking price elasticity. In an RP or SP survey, parking elasticity is derived from a discrete choice model capturing the effects of a price change on demand. The elasticity is converted from the price coefficient using an individual or aggregate formula [56]. In a before-and-after experiment, the point elasticity (at the new or the old price), the mid-point elasticity, or the log-arc elasticity formula is used [16]. In principal, the generalized travel cost and mode choice is observed in an RP survey. The coefficient of travel cost and alternative specific constant can be the estimated. The elasticity is derived from these estimates. Gillen (1978) used data from the 1964 Metropolitan Toronto and Regional Transportation Study to estimate a set of logit models. The elasticity measure of auto use with respect to parking costs was found to be -0.31 [26]. Analyzing observed responses to parking fees, Vaca and Kuzmyak (2005) estimate elasticity of parking demand to price in the range of -0.1 to -0.3 [54]. Proulx et al. (2014) have developed a mode and parking choice model on the basis of a biennial campus-wide transportation and housing survey at the University of California, Berkeley. They report that with a 10% increase in parking permit price, the drive-alone rate will drop by 3% [43]. In an RP survey, the reported choices of a traveler are made under real-world constraints and based on her knowledge of available travel options. It is the same in our experiment; the subject must report her commute mode after placing the ask. In addition, 12 weekly email RP surveys in our study ask the subject to report her commute modes for the previous week. However, in the RP survey, there is usually little chance of observing a wide range of price changes. The elasticity estimate heavily relies on the modeling assumptions. In addition, it is also difficult to use RP data to infer the causal impact of a new demand management strategies, such as a daily cash-out program, because no such actual alternatives are currently being offered. While RP studies typically examine consumed parking, SP studies potential parking demand. Researchers also use SP surveys to examine how transportation mode choice and parking preferences would shift under parking pricing scenarios that do not currently exist. As a result, the price coefficients estimated from SP data are likely to be more robust than those from models estimated from RP data [8]. Ng (2014) has used the same campus-wide RP data from Proulx's (2014) paper and conducted an additional SP survey with 4,188 campus employees. She estimated a parking price elasticity of -0.97 [39]. A meta-analysis of parking elasticity shown that elasticities based on SP data are more elastic than parking elasticities based on RP data [16]. The potential prevalence of hypothetical bias may cause differences between SP- and RP-based elasticities [17]. Because SP data are hypothetical, they might not adequately represent the alternatives as they actually would be presented and experienced if offered (e.g., market and personal constraints might not be accurately accounted for) [35]. There is also a risk that the survey respondents exaggerate their preferred behaviors because they would not want the employer to increase parking prices or to use the survey to determine their willingness to pay for employee parking. Thus, we have designed our experiment with the auction rule that the dominate strategy is bid the WTA to forgo parking. It is costly for subjects to exaggerate in our experiment. The TRACE (1999) study of transport elasticities notes that since 1985, almost all transport-related elasticities have been generated by some form of modeling [13]. The study's authors suggest that the empirical responses ex ante and ex post of a price change should be a good supplement for the survey-based parking market responses [29]. In a before-and-after experiment, elasticity is estimated by observing changes in occupancy concomitant with small changes of price. Kanafani and Lan (1988) have estimated parking price elasticity by regression based on the results of a series of price changes that took place at San Francisco airport [28]. The demand functions estimated imply a wide variation in parking price elasticity (from -3 to -0.30). Kelly and Clinch (2009) have measured price elasticity in the on-street parking market in Dublin city center when faced with a citywide increase of 50% in the hourly cost of on-street parking [29]. According to occupancy data collected before and after the price change, the average elasticity of demand was determined to be -0.29. Pierce and Shoup (2013) have measured price elasticity in the SFPark study, where the meter rate changes based on occupancy rates [42]. 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 the approach of ex ante and ex post demand analysis for the generation of price elasticities, attention was needed for extraneous confounding factors. Confounding factors 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 price elasticity was positive in many cases, so other factors must have overwhelmed the effects of prices on parking demand. As in the nature of before-and-after studies, these confounding factors are often hard to measure and control. Kelly and Clinch (2009) have 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 [29]. Our experiment explores a possible solution, the repeated second-price auction. The incentive response function is also the cumulative distribution function of employees' willingness to forgo parking. We measure the curve by measuring each subject's WTA through the repeated second-price auction. Our incentive offer is the auction mechanism, which remains fixed throughout the study. The incentive offer is then uncorrelated from any temporal confounding factors such as weather and special events. The effect of incentive is then separable.

A downside of our experiments is that the complicated auction process was confusing to the subjects at the beginning of the experiment. The mechanism confusion is explored in section 3.3. The biding result of the first month is generally biased due to misunderstandings of the auction mechanism. We issued a treatment that further explained the auction rule in the end of the first month. After that, the bids become meaningful. We had to relinquish one month of data due to this. Another downside of our experiments is the cost. To control the overall cost, we designed a \$15 maximum bid. The incentive curve is then partially measured between \$0 to \$15. The acquisition of this data cost an average of \$28/person/month. The parking incentive response curve is measured for a self-selected 215 subjects and is thus biased. We collect demographics through the entry and exit survey, and estimated a quantile regression to extrapolate our samples to the whole campus employee population. The confidence intervals of our estimates are wide due to the sample size. For example, we estimate that 18.2% of the faculty would forgo parking for a \$5 incentive on a cloudy Monday. The standard deviation of this estimate is 5.0%. For the staff cohort, this number is 13.7% with a standard deviation of 2.8%. The standard deviations can be reduced with a lager sample size.

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The report begins with a description of the experimental design, followed by a description of the subjects' socioeconomic characteristics in section 3.2. We then discuss the auction mechanism design and prove that it is truth-revealing in sections 3.2 and 3.2. The app and data collection system are introduced in section 3.2 . We describe the bid data and how WTA data was converted to daily incentive response curves in section 3.3. We estimate parking incentive elasticity and intensity in section 3.4. We build a quantile regression model in section 3.5 to extrapolate our subjects to the whole campus employee population. The last section is the conclusion.

3.2 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. Offering a parking incentive is effective in these employer-owned or leased lots. It is a better strategy than directly charging for parking at employment sites; a move to paid parking is likely to cause significant employee morale issues or where management. Offering parking incentives is also a good option when management, for whatever reason, is unwilling to ask employees to pay for parking. The FlexPassPlus study described in this section 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 at 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 2,958 employees who had already purchased a **C** or **F** permit for the entire 2015 fall semester. The study was conducted in the fall semester of 2015. The instruction days were from August 24 to December 11, 2015. The study covered three months in that period, from September 1 to November 30, 2015. During the study, the price was $95 per month for the **F** permit and $131 per month for the **C** permit. Study subjects could participate in 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 was compared to an incentive determined by a random number generator. If the subject's bid was lower than the incentive, he or she received the incentive and sold the parking privilege. If the subject's bid was greater than the incentive, he or she received nothing and sold nothing. Subjects bid against random numbers instead of unknown bidders. This sped up the auction process. We also built a smartphone-based data collection system to make bidding more convenient for our subjects.

Participant Recruitment

Subjects were recruited from the 2,958 employees who had already purchased a **C** or **F** permit for the entire 2015 fall semester. The recruitment emails are attached in appendix H. 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 (see appendix G) were compensated the same amount. Thus most subjects received $50 in Amazon gift cards in two installments. Among the 2,958 **C** and **F** permit holders at UC Berkeley that we reached through emails and postcards, 215 respondents finished the sign-up process to become subjects. Table 3.1 summarizes their demographic and socioeconomic information. UC Berkeley staff made up the bulk of the sample. Most subjects are over 25 and under 65 years old. Of the subjects, 42.2% had at least one bike while 38.5% had 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. The sampling bias is checked in terms of the permit type distribution. There are 163 **F** permit holders within our 215 subjects, which makes 75.8%. The total number of **F** permit holder population is 1,999, 67.6% of the all **C** and **F** permit holders. A Fisher test results in a p-value of 0.012. The sample selection bias is significant. More **F** permit holders enrolled in the study compared to the permit holder population.

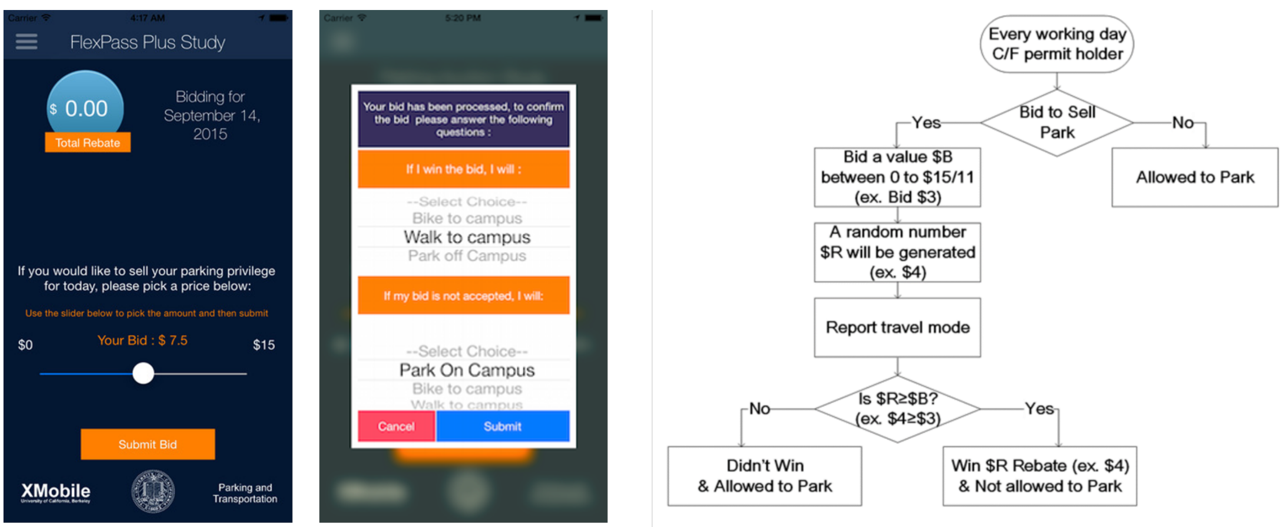
Auction Procedures

Study subjects were requested to download and install the FlexPassPlus app for their phone. Upon installation of the application, subjects had the opportunity to sell their parking on campus each working day (Mon. to Fri.) during the study period. Subjects could ask to be paid any amount up to $15 for their parking on campus for the day. After the subject submitted his or her ask, the app would choose a random amount as market price, uniformly generated, between $0 and $15. If the random amount was greater than or equal to the ask, the subject would win and the bid would be accepted at the random number. The research team then credited that random amount to the subject's account, and the subject would no longer be able to use his or her permit to park on campus that day. If the random number were less than subject's ask, or the subject did not participate that day, he or she was allowed to park on campus. Figure 3.1(a) illustrates the auction interface. To avoid the

Table 3.1: Sample Descriptive Statistics

	Study Subject		Permit Holder	
	Count	(%)	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	

default effect, the default bid was set at \$15. If subjects wanted to sell parking, they had to move the slider to bid. The app would also prompt the subject to report the mode he or she would use to get to campus or to indicate if not coming at all. Figure 3.1(b) gives the interface for travel mode report. For example, a hypothetical permit holder could submit that he wants to sell his parking access for Nov-11-2015 at \$3. Since the probability of any number generated between \$0 and \$15 is equal, the probability of him winning, in other words, that his price will be less than the random number and hence accepted, is 80%. The higher his price is, the less chance he will win. However, if his price is too low, he may end up taking transit to campus with only \$1 compensation. The best strategy, therefore, is to bid the amount that he is truly willing to accept to forgo parking. For example, it may cost him \$10 to take transit (say \$5 for ticket and \$5 for the other costs, such as extra travel time and walking). In that case, submitting his price at \$10 maximizes his net benefit. The chart in Figure 3.1(c) illustrates the procedure for selling parking access and possible outcomes.



(a) (b) (c)

Figure 3.1: App screens and auction flow chart

Subjects' responses regarding whether or not they were parking on a given day were uploaded to the server through the FlexPassPlus app and sent to parking enforcement officers. If subjects sold their parking access, but parked on campus, they would potentially receive a parking citation. Subjects could bid on the following day starting at 12:01 pm. The auction ended at 12 pm of that day. The time of 12 pm was chosen because most employees commute to campus before 12 pm. This deadline ensures enough time for subjects to make a commute decision and bid. Once subjects submit their ask for a given day, subjects cannot change it or participate again. This design was arranged to be truth revealing. If a subject had not bid for the next day by the previous evening at 6 pm, he or she received a notification on the phone reminding the subject to do so.

Auction Mechanism

Table 3.2: List of Variables

	Description
M	the set of all travel modes, $m \in M$
i	the incentive ($)
$u : M \times R \to R$	utility function of commuting
PC	drive and park on campus
A	the set of alternative modes, $a \in A$
$\widetilde{V} : A \to R$	value of parking given a certain alternative mode $a \in A$
W	the value of benefit of forgoing parking
R	the random number generated in our auction. $f(.)$ is its p.d.f.
b	the ask ($)
$\bar{\theta}$	maximal bid
V	value of parking
$\Omega : A \to R$	the maximal benefit from the auction of choosing an alternative mode $a \in A$

Let $u(m, i; X)$ denote the utility of commuting of 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 provided in dollar value. u is assumed to be increasing in i, $\frac{\partial u}{\partial i} > 0$ (monotone assumption). X captures all other features related to travel behavior, such as 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:

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

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 setup of our second-price auction. The subject can ask for a price b between \$0 to $\$\bar{\theta}$. After that, a random number R will be generated. Denote the probability density function (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 lose 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 decisions: 1) decide whether to participate in the auction or not, 2) choose the alternative mode if the privilege of parking is sold (choose a from A), and 3) place an ask (choose b from $[0, \bar{\theta}]$). First, for any given a, we will prove the dominant 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 $b^*(a;X) = max\{min\{\widetilde{V}(a;X),\bar{\theta}\},0\}$. If the WTA to forgo parking with alternative mode a is within the range of $[0,\bar{\theta}]$, the dominant 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 participate in 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 measurement for the utility difference between park-on-campus and alternative mode a. The proof is attached in appendix 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 a incentive i has the same influence among 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. We define $a^*(X) = \arg\min_{a\in A}\widetilde{V}(a;X)$. Under the assumptions of monotonicity and additive separability, $a^*(X)$ dominates all other modes in the choice set A. $a^*(X) = \arg\max_{a\in A} u(a,i;X)$ for all incentive i.

After placing the optimal ask $b^*(a;X)$ is placed, the expected net benefit becomes a function of a and X. We apply the 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. Applying the monotone assumption, it follows that the dominate alternative mode $a^*(X)$ maximizes $\Omega(a;X)$.

In the second-price auction experiment, 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 he or she wins the auction. Otherwise he or she will park on campus. We can extract the following information: 1) the subject is indifferent between parking on campus and taking transit plus receiving \$10; 2) among all alternative modes, the subject prefers transit. The former fact is based on the monotone assumption. The latter is based on both monotone and additive separability assumptions.

Software System for Data Collection

A smartphone-based software system, shown in Figure 3.2, was designed to collect WTA 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 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.

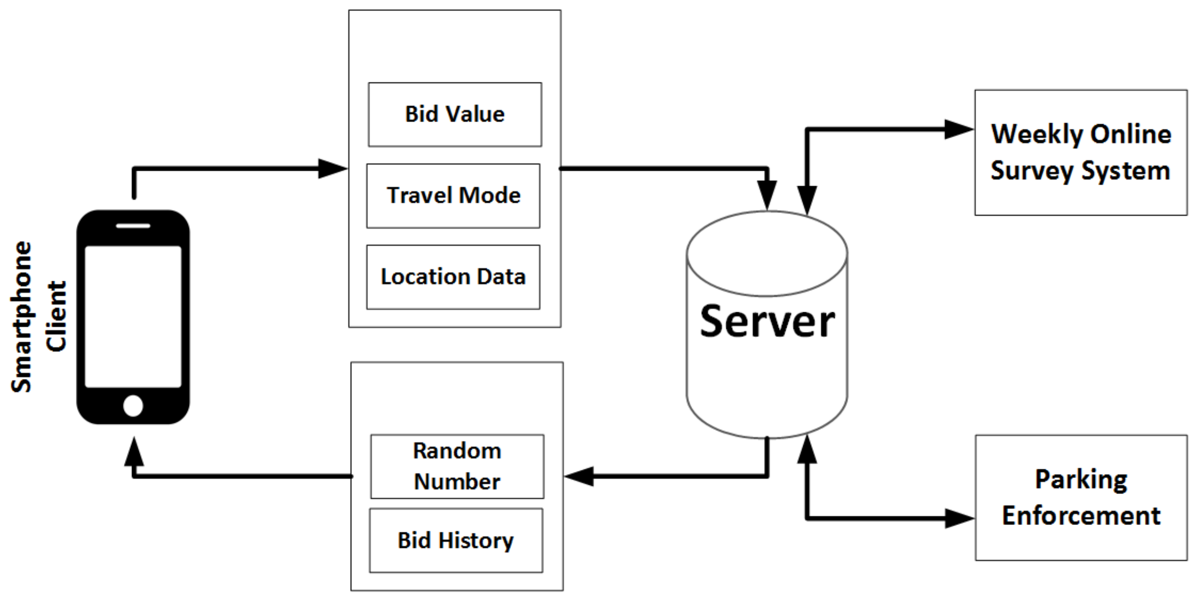


Figure 3.2: Software system for data collection

3.3 Data Description

During the three-month study period, on every day, 215 subjects may decide whether to participate in 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 loses, $m_{l,ij}$. 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 lose-mode $m_{l,ij}$. If the lose-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 away form school 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 lose-mode is Park-on-Campus, they should bid a positive amount. Violin plots in the upper part of Figure 3.3 illustrate the bid distribution of the two groups for each day. The violin plot is similar to box plots, except that it also demonstrates the probability density of the data at different values. The bold bar represents the median of the bids. Different widths at different bid values represent the kernel density estimation results. 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 September 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 did not need to park. On October 7, one month after 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 the "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 was followed with a slider 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 bid above \$2, he or she saw on the next screen: "You are leaving money on the table." We then explained the auction rules again, emphasizing that the subject was bidding against a random number. The upper part of Figure 3.3 demonstrates that after the Hawaii treatment, the blue bar became close to zero and it continued to the end of the study. It is believed that most subjects understood the auction rule and were bidding their true value of parking. The rest of this paper will only analyze the data collected after the Hawaii treatment, from October 8 to November 30. The lower part of Figure 3.3 reveals the number of subjects who participated in the auction each day. There were 23% subjects participating in the study each day on average and no significant dropout being observed.

Bid value should also be affected by the alternative mode. It is shown in Table 3.3. Row names stand for win-modes while column names for lose-modes. The numbers after the \$ sign give the median bid. The numbers in parentheses are 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 would not commute no matter win or not. The median bid of these 773 bids is \$0.5. Subjects reported 132 times that they would park on campus

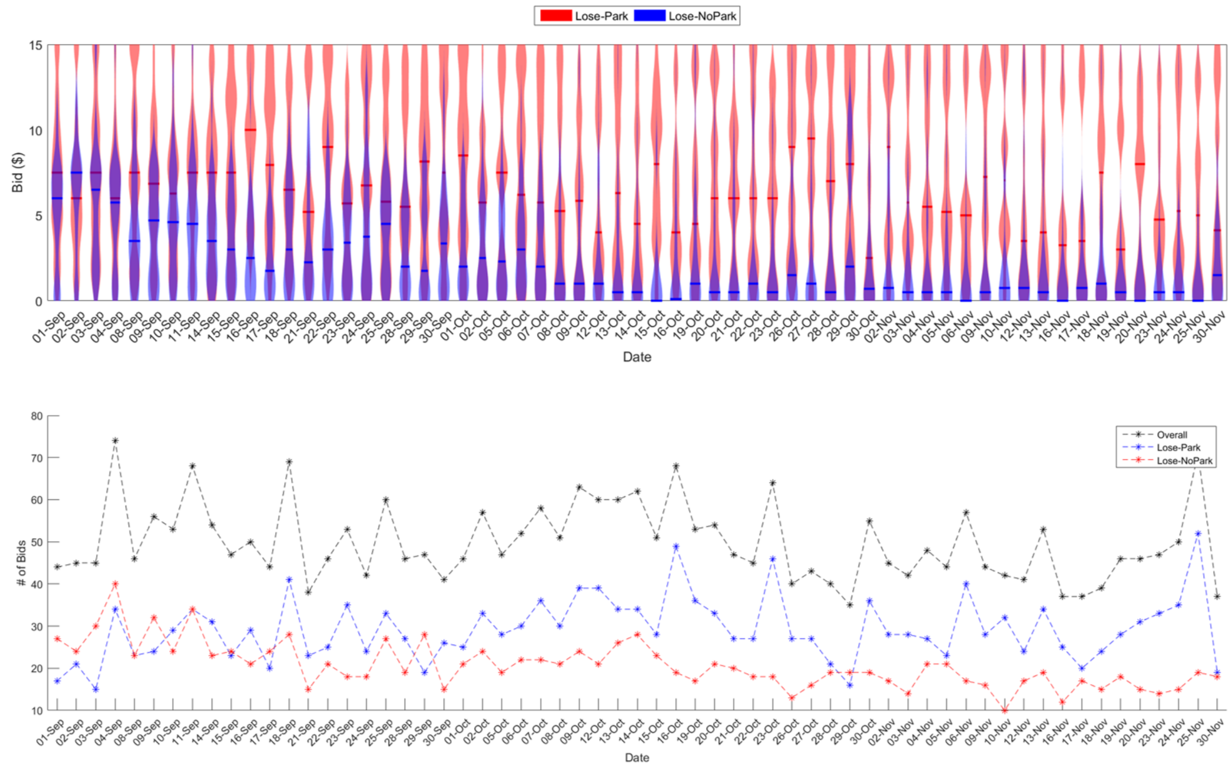


Figure 3.3: Bid distribution and participation

if losing the auction and not commute if winning the incentive. The median bid of these 132 bids is \$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; this question requires further investigation and is beyond the scope of this dissertation. Table 3.3 again indicates that subjects understood the mechanism and bid their true WTA to forgo parking.

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 holder, our study directly measures the incentive response curve.

Table 3.3: Bid Value and Commute Mode. (Row names are for win-modes while column names are lose-modes. Number after the $ sign gives the median bid. Number in the bracket gives the number of bids.)

	NO COMMUTE	OTHER TRANSPORT	TRANSIT ONLY	BIKE AND TRANSIT	PARK OFF CAMPUS	CAR-POOL	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)

The empirical distribution of bid values is shown in Figure 3.4, 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 bidding their true WTA to forgo parking, Figure 3.4 is also the incentive response curve, where the x-axis can be named as incentive rate, I, and the y-axis as percentage of subjects not parking on campus, $S(I)$. For example, on an average Friday, 20% percent subjects bid under \$5. This fact also means that if offered a \$5 incentive on Friday, 20% percent of subjects will accept it and forgo parking. If the same reduction needs to be achieved on Thursday, the incentive level should be raised to \$10.5. The power of incentive, parking demand reduction *caused* by incentive, can be extracted from the response curve. The percentage of subjects not parking 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 on Monday to Thursday. Friday is typically the day for discussions and group meetings. Thus subjects have more flexible schedules. Figure 3.4 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 than offering a flat rate. The next section will further explore the demand reduction function, $R(I)$, by building up explanatory models.

3.4 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 [42, 29]. This yields the equation

$$\log R_{jk} = \alpha + \beta \log I_{jk} + \varepsilon_{jk} \tag{3.1}$$

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_ij... $R_{jk} = \sum_i 1\{b_{ij} \leq I_{jk}\}/N - \sum_i 1\{b_{ij} = 0\}/N$ 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 even if there is no incentive, $S_j(0)$.

The first row of Figure 3.5 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 versus log-reduction curves. It can be observed that the incentive response curves vary greatly but the log-reduction versus log-incentive curves share a similar shape, linear. The red lines are ordinary least square (OLS) fits using regression equation 3.1. In the OLS regression, we assume the noise term ε_{jk} is i.i.d. across different incentive levels and days. However, Figure 3.5 shows that the gray curves in log-log

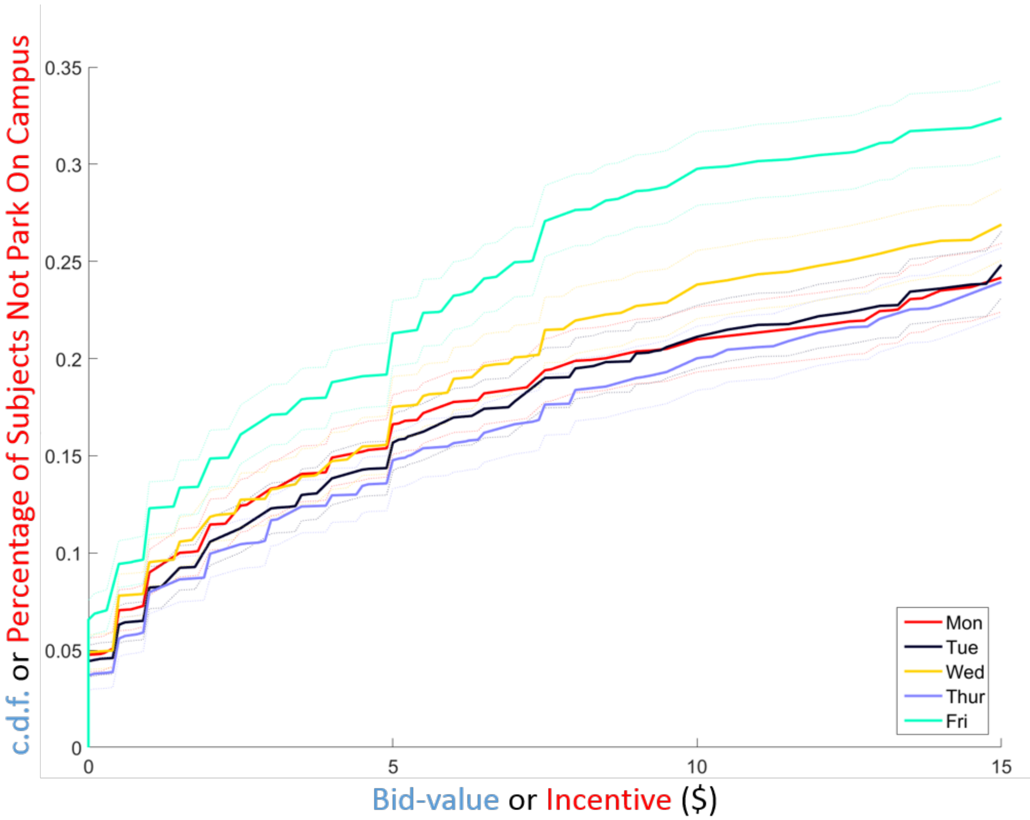


Figure 3.4: Bid distribution or incentive response curves

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 3.1 to a mixed linear model,

$$\log R_{jk} = \alpha + A_j + \beta \log I_{jk} + \varepsilon_{jk} \tag{3.2}$$

where α is the average intensity for all days, and A_j is a day-specific deviation from α. We first assume A_j is a fixed effect, a constant for day j. An 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 model is preferred due to higher efficiency.

The regression result is given in Table 3.4. There are four models, the baseline-model, weekday-model, weather-model and weekday-weather model. The baseline regression equation is given in equation 3.2. 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 $Weekday$ takes value from Monday to Friday. Four 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

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

The estimation result of this baseline random effect model is given in first column of Table 3.4. The average parking incentive elasticity is 0.514. With a 1% increase in the incentive, parking demand will reduce by 0.514% 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 [40]. 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%.

Figures 3.4 and 3.5 reveal that incentive response curves differ by weekdays. The second column in Table 3.4 illustrates 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 near the Friday's. 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. A likelihood ratio test indicates that the model with weekday effect is significantly improved from the baseline model in column (1). Column 3 of Table 3.4 evaluates the effect of weather on the incentive response function. A 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.

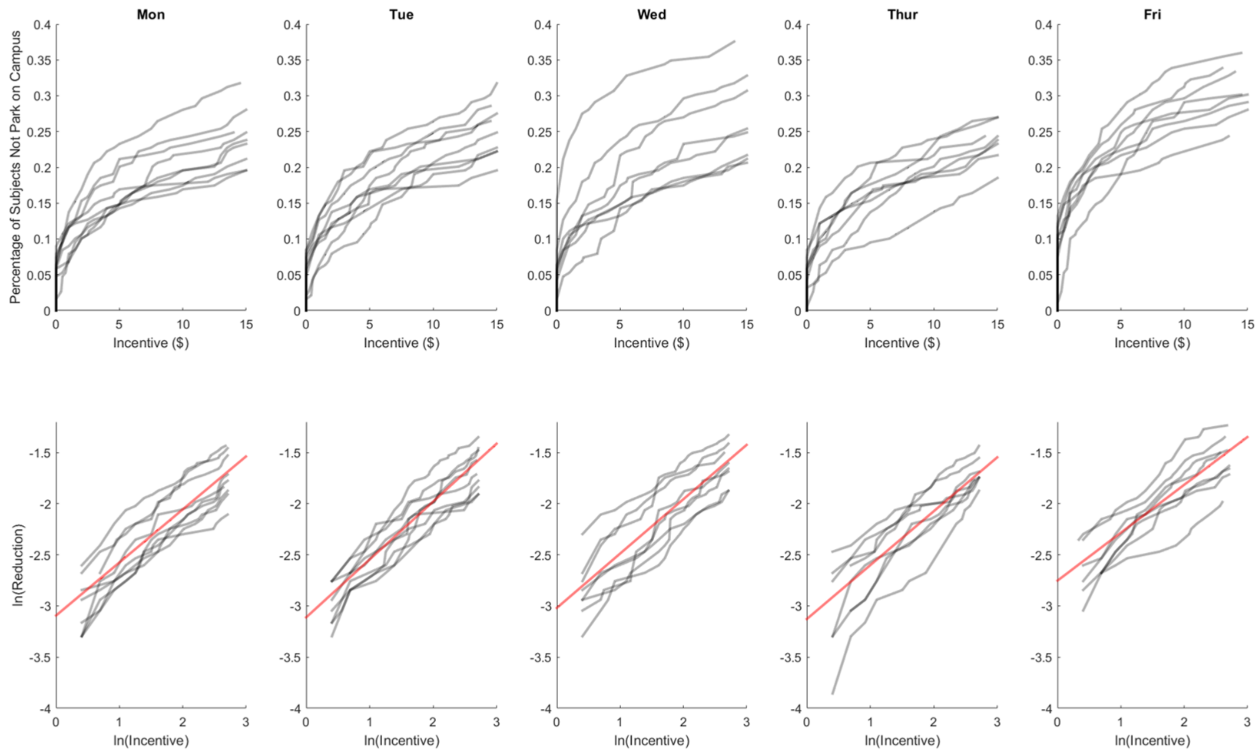


Figure 3.5: The first row depicts incentive response curves for every day divided by weekdays. Each curve stands for a day in the study. The second row depicts log reduction versus log incentive. The red line is the ordinary least square fit.

Compared to clear weather days, on cloudy or rainy days elasticity is significantly higher by 0.073. The full model that accounts both weekday and weather effects is given in column (1) of Table 3.4. A likelihood ratio test reveals that the full model is significantly improved from the model with only weekday or weather effect. Compared to the 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 days, on cloudy or rainy days 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 Fridays, with a \$10 incentive, the median demand reduction is estimated as $exp(-2.877 + 0.489 * ln(10)) = 17.36\%$. On cloudy Fridays, this number is $exp[-2.877 - 0.334 + (0.489 + 0.084) * ln(10)] = 15.08\%$. As incentive rate rises, the difference will becomes smaller. At a \$15 rate, the demand reduction under clear weather becomes $exp(-2.877 + 0.489 * ln(15)) = 21.17\%$. On cloudy days this number is $exp[-2.877 - 0.334 + (0.489 + 0.084) * ln(15)] = 19.03\%$. Although the elasticity on cloudy days 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 3.5 illustrates the heterogeneity of parking demand reduction. The regression model in Table 3.4 demonstrates that parking incentive elasticity stays rather constant under various weekday and weather conditions. However, parking incentive intensity varies greatly, which accounts for the variation in parking demand reduction.

Case Study: Auction versus Before-and-After

Our study measures the subjects' daily WTA. Section 3.3 demonstrates that given an incentive level on a certain day, we can calculate the parking demand by summing up the number bids (or WTAs) below that incentive level. It becomes feasible for us to simulate the result of before-and-after experiments. We define the "before" stage to be October 8 to October 31. The incentive rate for the "before" stage was $6 per day. We define the "after" stage to be November 1 to November 30. The incentive rate for the "after" stage was doubled, $12 per day. We computed the parking reduction amount for each day of the two stages based on the WTA data we collected. The result is provided in Figure 3.6. The solid blue line represents the parking demand reduction under the $6 per day incentive. The dashed blue line represents the average reduction in the "before" stage. The solid and dashed red lines present the daily reduction and average reduction in the "after" stage. Applying a two-sample t-test, the demand reduction after doubling the incentive is insignificant. One possible explanation is that there were more cloudy and rainy days in November. We ran a regression by controlling for the weekday and weather. The estimate of incentive elasticity turns out to be -0.028 with a 95% confidence interval of (-0.4259, 0.3699), which is not significantly greater than 0. There must have been other factors, such as campus events, influencing the parking but not being observed. It is then difficult to isolate the impact of raising the incentive. As described in section 3.4 when we estimate the elasticity based on the auction data, the incentive is uncorrelated with temporal confounding factors. We estimate a parking elasticity of 0.514, with a 95% confidence interval of (0.504, 0.524).

3.5 Extrapolation

Policy-makers would like to know the incentive response curve for the entire permit holder population. We denote it as $F_v(I)$. $F_v(I)$ is also the c.d.f. of a permit holder's WTA to forgo parking. We estimate a quantile regression model in this section from our sample of 215 subjects. It models the distribution of a permit holder's value of parking conditioned on her demographics and travel attributes, $F_v(I|X)$. X is a vector of observed permit holder demographics and attributes of travel. After observing the distribution of X for the permit holder population, the incentive response curve can be computed as $F_v(I) = E_X[F_v(I|X)]$.

We use self-selection sampling in out study. This strategy enjoys the advantage of reducing the amount of time searching for appropriate subjects. The subjects are also likely to be committed to take part in the study, which can help in improving participation. However, it suffers from the disadvantages of self-selection bias and the sample not being representative.

Table 3.4: 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

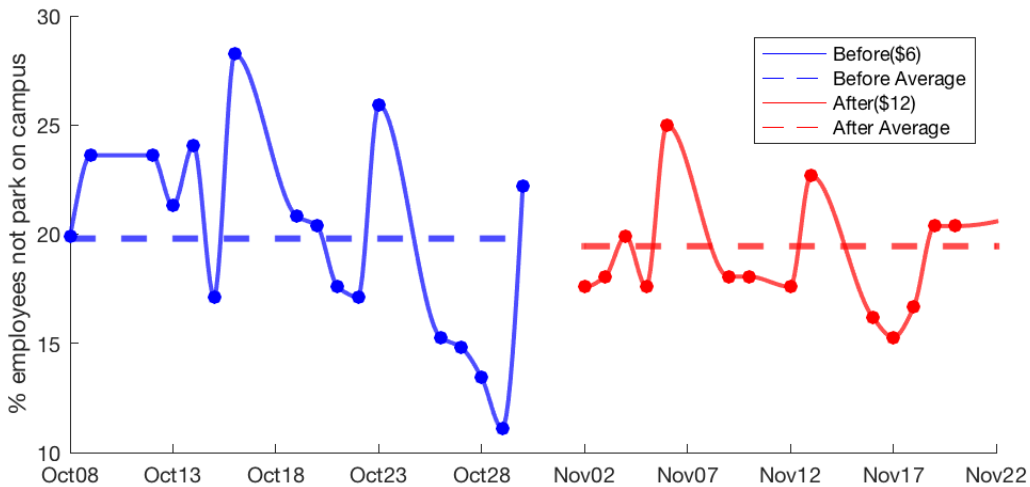


Figure 3.6: Parking demand reduction under a simulated before-and-after experiment.

In our case, the Pearson test in the participant recruitment section indicates a selection bias. **F** permit holders are more likely to be enrolled. We estimate a quantile regression model that can be used to extrapolate our sample result to campus permit holder population. A permit holder values her campus parking at the rate of \$$v(X, \xi)$. ξ is a random vector modeling unobserved permit holder demographics and attributes of travel. x is a realization of the random vector X. $F_v(I|x) = P\{v(x, \xi) \leq I\}$ is the c.d.f. of $v(x, \xi)$. The τth quantile of $v(x, \xi)$ is given by $Q_v(\tau|x) = F_v^{-1}(\tau|x) = \inf\{I : F_v(I|x) \geqslant \tau\}$. $Q_v(\tau|x)$ is the conditional quantile function (CQF) of $v(x, \xi)$. It can be interpreted to mean that a permit holder with condition x would forgo parking with probability τ for incentive $Q_v(\tau|x)$. We assume x is a i.i.d. draw of X and ξ is independent of X. We can then compute the incentive response curve, $F_v(I)$, for the permit holder population by averaging X. $F_v(I) = E_X[F_v(I|X)]$. As $F_v(I)$ is nondecreasing in incentive rate I, we can estimate $F_v(I)$ by estimating its inverse function $Q_v(\tau) = E_X[Q_v(\tau|X)]$.

We estimate the CQF, $Q_v(\tau|X)$, through a quantile regression model. The CQF solves the following minimization problem,

$$Q_v(\tau|x) = \arg\min_{q(x)} E[\rho_\tau(v - q(x))]$$

where $\rho_\tau(u) = (\tau - 1(u \leq 0))u$ [30]. If $\tau = 0.5$ this becomes least absolute deviations because $\rho_{0.5} = 0.5|u|$. In this case, $Q_v(\tau|x)$ is the conditional median since the conditional median minimizes absolute deviations. In order to estimate the CQF, we assume $q(x)$ is linear, producing

$$\gamma_\tau = \arg\min_{b \in R^d} E[\rho_\tau(v - x'b)]$$

The quantile regression estimator $\hat{\gamma_\tau}$ is the sample analog of γ_τ. It turns out this is a linear programing problem that can be solved by the simplex method. The demographic and travel attributes (X) we consider are age, income, occupation, day of the week and weather. These demographics are collected in the entry survey described in section 4.1. These explanatory variables are chosen because they are also available at the population level. The regression equation is:

$$
\begin{aligned}
q(X) = \gamma_0 &+ \gamma_{Age} Age + \gamma_{Income} Income + \gamma_{Faculty} 1\{Job = Faculty\} \\
&+ \gamma_{Weekday} Weekday + \gamma_{CloudyorRainy} 1\{Weather = Clouldy | Weather = Rainy\}
\end{aligned}
$$

The estimation result of the quantile regression is given in Table 3.5. Condition quantile function is estimated from the 6% to 20% quantile. Below 6%, most of the values, v, are 0. Above 20%, most of the them are truncated at \$15. Ten percent, 15% and 20% quantiles are reported in table 3.5. We use the 20% column as an example to interpret this table. The baseline cohort is a subject under 34-year-old, within a household annul income level of \$81k to \$100k, being a staff, and commuting on a clear Friday. Offered a \$7.5 incentive, shown in the "Constant" row, 20% of this cohort forgoes parking on campus. For the same sub-population, if commuting on Thursday, to achieve the same reduction, the incentive should be raised by \$5.0. The difference is highly significant. If on a cloudy or rainy day, the incentive should be raised by \$1.9. Compared to staff, a faculty member asks for \$5.4 less. Faculties, in general, have more flexible schedules and are willing to forgo parking at a lower incentive rate. For age groups, there is no significant difference in terms of value of parking for subjects under 54. Subjects from 55 to 64 years old give a significantly higher value to parking. Subjects at full-benefit retirement age, 65 or above, value the privilege of campus parking significantly less. The median household income of our subjects is \$81k to \$100k. The \$61k to \$80k cohort does not significant differ from that. The low-income population, under \$60k, requires \$5.3 less to reduce the same amount of parking (20%). This result may be caused by their lower value of time. The cohort with income from \$101k to \$120k should have a higher value of time but still values campus parking less than the \$81k to \$100k cohort. The difference is \$4. This may result from the fact that they live closer to campus and the time cost of not parking on campus is relatively small. For the high-income population, \$121k and above, the difference becomes insignificant. Further analysis can be conducted after extracting commute distance from the smart-phone location data.

We conducted a case study to test the performance of the quantile regression model with 70% of the data randomly selected as a training set, and the rest as the testing set. The quantile regression models in Table 3.5 are estimated based on the training data. A quantile function for subject i on day j in the testing set was predicted based on the model, $\hat{Q}_v(\tau|x_{ij})$. We then computed the incentive response curve for cloudy or rainy weather for the entire data set. We first computed the population quantile function by conditioning and averaging, for example, $\hat{Q}^p_v(\tau|Cloudy\ or\ Rainy)$. The unbiased estimator for the conditional incentive

Table 3.5: Quantile Regression Results

	Dependent variable:		
	Quantile or Incentive ($)		
	10%	15%	20%
Weekday (Friday)			
Mon	0.435	1.595*	3.036***
	(0.347)	(0.849)	(0.670)
Tue	0.283	1.119	2.536***
	(0.279)	(0.699)	(0.837)
Wed	0.283	0.976	2.469***
	(0.258)	(0.677)	(0.810)
Thu	0.826**	2.286***	4.969***
	(0.420)	(0.830)	(0.639)
Age Group (under 34)			
35to44	−0.283	−0.119	0.495
	(0.320)	(0.742)	(1.081)
45to54	−0.217	−0.071	0.438
	(0.352)	(0.700)	(1.061)
55to64	0.500	4.667**	2.536**
	(0.397)	(1.849)	(1.025)
65+	−0.543	−1.024	−3.000***
	(0.485)	(0.717)	(1.161)
Income Group (81k to 100k)			
Under60	−1.000**	−3.500***	−5.250***
	(0.435)	(1.128)	(1.000)
61to80	−0.100	−0.500	−0.500
	(0.560)	(1.260)	(0.961)
101to120	−1.000**	−3.500***	−4.010***
	(0.446)	(1.059)	(0.973)
121+	−1.000**	−2.500**	−1.510
	(0.457)	(1.045)	(1.028)
Faculty (Staff)	−0.217	−2.310***	−5.438***
	(0.278)	(0.609)	(0.765)
Cloudy or Rainy (Clear)	0.565*	0.976	1.933***
	(0.332)	(0.740)	(0.480)
Constant	1.043**	4.381***	7.531***
	(0.417)	(1.162)	(1.028)
Note:			*p<0.1; **p<0.05; ***p<0.01

response curve, $\hat{S}(I|Cloudy\ or\ Rainy)$, is the inverse function of $\hat{Q}_v^p(\tau|Cloudy\ or\ Rainy)$. We compared the estimated CQF to the ground truth one, which is the empirical c.d.f. of raw bids collected on cloudy or rainy days; see Figure 3.7(a). The black line indicates the estimates and the red line the ground truth. The shaded region indicates one standard deviation around the ground truth. Similarly, Figure 3.7(b) shows the incentive response curve for the senior cohort, $\hat{S}(I|55 \leq Age \leq 64)$. The estimates are within the 95% confidence interval which indicates good extrapolation.

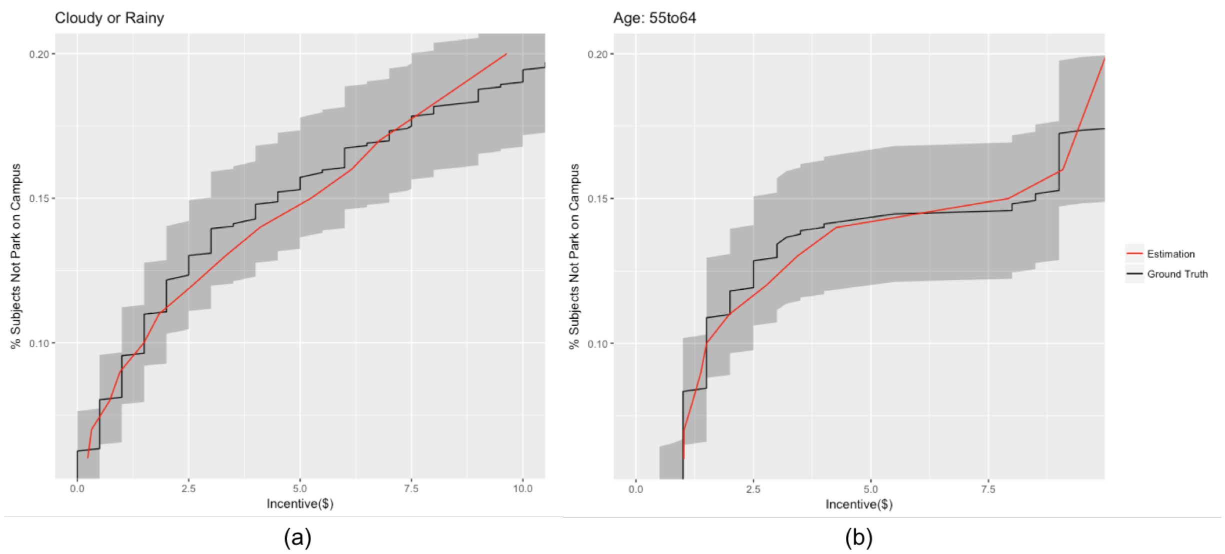


Figure 3.7: Incentive response curve estimations based on the quantile regression model. The shaded region indicates 95% confidence interval.

3.6 Conclusion

We designed the FlexPassPlus study to learn the parking incentive response curve. This curve is also the c.d.f. of employees' WTA to forgo parking. We generated a direct measurement of this curve by collecting each employee's WTA through a repeated second-price auction. The auction uses the BDM mechanism. We prove that our variation is incentive-compatible, which means employees will bid their true WTA in the auction. By checking the daily bidding results and issuing survey quizzes, we confirmed that the subjects understood the auction rules and reveal their true preference. For instance, subjects whose alternative is to not commute have a median WTA of $2.25. For those whose alternative is to take transit, the median WTA is $9.50.

Since the auction was repeated daily, we were able to measure a separate incentive response curve for each day. We conducted a random effect regression to estimate the average parking incentive elasticity, which is 0.514. The standard deviation for this estimate is 0.005, which is more robust than other estimates in the literature. Confounding variables in the before-and-after study, such as weather condition, become explanatory variables in the FlexPassPlus study. Therefore, we can infer that the variations in intensity are due to weekday and weather, while the elasticity stays rather invariant. When the incentive rate is under $20 per day, the variation of intensity is much higher and dominates the variation of elasticity. The elasticity is significantly higher on cloudy or rainy days (by 0.084) compared to on clear days. The intensity is significantly lower on cloudy or rainy day by 0.334.

We estimated a quantile regression model to extrapolate our sample to the entire population. It models the distribution of an employee's WTA conditioned on her demographics and travel attributes. For example, for age groups, there is no significant difference in terms of value of parking for subjects under 54. Subjects from 55 to 64 years old have a significantly higher value of parking. Subjects at full-benefit retirement age, 65 or above, value the privilege of campus parking significantly less. We conducted a case study to test the performance of the quantile regression model. The ground truth is within the 95% confidence interval of the estimation, which suggests good extrapolation. 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.

Chapter 4

Designing the Incentive Response Curve with the SPA Data

In this chapter, we design daily parking cash-out programs for the UC Berkeley campus based on the incentive response curve measured by the second-price auction(SPA) experiment.

4.1 Literature Review

In most employer-owned parking lots, where permit prices are below market, parking cash-outs are effective. This chapter focuses on the design of a program that can reduce congestion in parking lots. A fixed-cost monthly parking pass is one of the most widely implemented demand management solutions on college campuses [5]. Such a monthly permit can be re-designed to reward regular parkers with reduced costs or rebates for days they do not park. A daily cash-out provides both incentive and flexibility and is more likely to shift commuter mode choice [31]. A daily parking cash out program, the PayGo Flex-Pass, was tested in Minneapolis, Minnesota, in 2010 and 2011 [31]. It provided a rebate of $7 on days when parking was not used. Thirty-one subjects were enrolled in the study for 5 months. The PayGo Flex-Pass led to a decline in driving days from 78.5% to 56.5%. In chapter **??**, we introduced our daily parking cash-out program, the FlexPass. We conducted an RCT with 392 subjects over a period of three months to estimate its causal impact. We estimate the FlexPass causes a highly significant reduction of 6.1% in parking consumption. The question then arises: what will be the treatment effect if incentives are provided at higher levels, and what is the optimal cash-out? The parking incentive response curves generated by the SPA experiment provide answers to these questions.

In Berkeley, the cost of new space is high, with construction cost penciled at $65,000 per space and land costs of $7,000,000 per acre [53]. The university is expanding and the high cost of acquiring new land is a constraint. Several parking lots have been removed to build new classrooms, student centers, and the new Berkeley Art Museum. This exacerbates the parking problem. While the campus population is increasing, the Parking and Transportation (P&T) department wants to control campus parking demand and stop building new parking lots. Their objective is to keep the parking occupancy at a certain level, for example, 85%, in order to provide a good parking service. Demand above that level will increase the parking cruising time. Demand below that level will result in empty spaces and revenue losses. Therefore, we design our daily parking cash-out program to minimize the cruising and excess spaces.

4.2 Design Daily Incentive Scheme

Based on the SPA experiment, we design a daily parking cash-out program with variable daily rates. The pricing process is modeled as a signaling game with two players. Player 1, P&T, is the sender and player 2, permit holders, are receivers. At stage 0, P&T observes the parking incentive response curves from the SPA experiment. At stage 1, P&T chooses the daily incentive rate. The game continuous to stage 2. At stage 2, permit holders, having observed the incentive scheme, choose their consumption of parking. For a certain permit holder on a certain day, he or she will compare the incentive rate with his or her WTA of that day. If the incentive is higher than WTA, the permit holder will accept it and not park on campus. P&T should choose the incentive to reduce parking to a certain targeted level. The cost function for P&T is the following:

$$K(I) = hE\left[(S(I) - r)^+\right] + pE\left[(S(I) - r)^-\right]$$

where:
r is the targeted reduction level per day. For example, the r to maintain an 85% occupancy is 15%. $S(I)$ is the percentage of permit holders not parking on campus under incentive rate I. $S(I) = N_{np} + e^{\alpha+\varepsilon} I^{\eta}$. ε is normal distributed with mean 0 and variance σ. $(S(I) - r)^+$ denotes $\max(S(I) - r, 0)$. It is the left over parking inventory. When the reduction $S(I)$ is higher than the targeted level, $S(I) - r$ spaces will not be used. $(S(I) - r)^-$ denotes $\max(r - S(I), 0)$. It is the excess demand or parking congestion. When the reduction, $S(I)$, is less than the targeted level, $r - S(I)$ permit holders will have difficulty finding parking spaces. h is the inventory cost. It is the cost of keeping 1% of the spaces empty. p is the congestion cost. It is the cost of having 1% of the permit holders cruising for parking or double parking.

First we consider a fixed rate scheme, where the incentive rate is fixed for all days. Checking the first order condition, the optimal incentive rate is given by

$$ln(I_{opt}) = \frac{ln(r - N_{np}) - \alpha - Z^{-1}(\frac{h}{p+h})\sigma}{\eta}$$

where Z^{-1} is the reverse cumulative distribution function (c.d.f.) of a standard normal random variable. If the gap between the targeted reduction level, r, and the reduction level without incentive, N_{np}, is huge, a large incentive is needed to achieve the targeted reduction. When the intensity α is higher, the baseline reduction is higher and a lower incentive level is required. When the elasticity η lowers, drivers are less sensitive to the incentive and a higher incentive level should be offered to achieve the targeted reduction. As the reduction is considered a random variable, the weight between h and p and the variation of ε also plays an important role. In terms of p and h, only the ratio p/h matters. When p/h increases, the inverse c.d.f. $Z^{-1}(\frac{h}{p+h})$ decreases, which leads to a higher optimal incentive level. Intuitively, when the penalty cost of the unsatisfied demand, p, is higher compared to the space holding cost, h, parking providers would like to eliminate congestion. Thus a higher incentive should be offered. When p is greater than h, $Z^{-1}(\frac{h}{p+h})$ is negative and a higher variance, σ, leads to a higher incentive level. Otherwise, $Z^{-1}(\frac{h}{p+h})$ is positive, a higher σ leads to a lower incentive level.

Studies in parking pricing indicate that fixed-price parking, across time and geography, without respect to demand or inflation, falls far short of its potential as an effective demand management tool. Ongoing performance-based pricing studies charge variable parking rates to achieve desired occupancy level. Without the information of the price response curve, most performance-based pricing studies, including the SFPark and the Seattle study, set rates empirically [20]. In the SPA experiment, the parking incentive response curve is estimated for different weekdays and weather conditions. The percentage of permit holders not parking on campus, S, is modeled as a function of incentive level, $S(I)$, in model(1) of Table 3.4. Model(2) takes weekday into consideration, which leads to $S(I; W_{eekday})$. Model(4) further considers the effect of weather, which leads to $S(I; W_{eekday}, W_{eather})$. It provides flexibilities in the incentive scheme design. P&T could set up different incentive levels on different weekdays or under different weather conditions. The following case study illustrates that with further understanding of the incentive response curve, better schemes can be designed that achieve higher performance.

In this case study, we assume $h = q = 1$, where the cost of the congestion and the left over inventory is weighted equally. Three targeted reduction levels, r, are studied: 10%, 15%, and 20%. For each targeted reduction, three kinds of schemes are designed based on three different incentive response models in Table 3.4. Scheme-1 is a fixed rate scheme. In Scheme-2, the incentive rate changes from Monday to Friday. Scheme-3 considers both weather and weekday conditions. All the schemes are depicted in Table 4.1. The optimal incentive rates are rounded to the nearest quarter. The incentive response models are estimated using the WTA data collected in October 2015. The performance of different schemes is evaluated using the WTA data collected in November 2015. The performance metrics are average congestion and average left over inventory. Given incentive I_j on day j, the percentage of permit holders not parking on campus is $S_j = \frac{1}{N}\sum_i 1\{WTA_{ij} < I_j\}$. The average congestion is calculated as $\frac{1}{D}\sum_{j}(S_j - r)^{-}$, where D is the total number of days in the test set. The average left over inventory is calculated as $\frac{1}{D}\sum_{j}(S_j - r)^{+}$.

There were 2,958 regular monthly permit holders in UC Berkeley in 2015. On the supply side, we assume that P&T wants to keep 2,366 spaces that can serve 80% of the permit holder population. That requires a 20% reduction. Figure 4.1 illustrates the daily parking demand reduction induced by Scheme-1 and Scheme-3. The purple area represents the percentage of permit holders not parking on campus regardless of incentive, $S(0)$. The red line is the targeted level, 20%. The yellow area represents the parking demand reduction induced by Scheme-1. The percentage of drivers relinquishing parking under Scheme-1 fluctuates widely around the 20% line. On Friday, many spaces remain empty, while on other weekdays, some drivers can hardly find parking. The green area is the parking demand reduction induced by Scheme-3. Compared to the yellow area, the reduction is closer to the targeted level on most days. Friday peaks are lower and gaps on other weekdays are filled. Scheme-3 leads to a lower congestion and fewer empty spaces. Table 4.1(c) illustrates that under a fixed-rate scheme, Scheme-1, the average congestion is 1.83% per day. This converts to 54 (2,958*1.83%) drivers who cannot find parking. The average left over inventory is 2.03% per day, which is 60 (2,958*2.03 %) empty spaces. If we apply Scheme-2, the average number of unhappy drivers and empty spaces will be reduced to 38 drivers per day and 46 spaces per day on average. If Scheme-3 is implemented, these two numbers will be further reduced to 34 drivers per day and 43 spaces per day on average. Averaging over all targeted reduction levels, and comparing to the fixed rate scheme (Scheme-1), Scheme-2 reduces the overall cost by 14.2% and Scheme-3 by 19.6%

Table 4.1: Incentive Schemes for Different Reduction Levels

(a) : Targeted reduction %10

Weekday	Scheme-1	Scheme-2	Scheme-3	
			Clear	Cloudy
Mon	$1.25	1.50	1.00	1.75
Tue		1.25	1.00	1.75
Wed		1.00	1.00	1.50
Thur		1.50	1.50	2.25
Fri		0.75	0.75	1.50
Average Congestion (%/day)	2.80	1.22	1.15	
Average left over inventory (%/day)	0.40	0.70	0.75	

(b) : Targeted reduction %15

Weekday	Scheme-1	Scheme-2	Scheme-3	
			Clear	Cloudy
Mon	$4.50	5.25	4.25	6.25
Tue		4.75	4.25	6.25
Wed		3.75	3.50	5.25
Thur		5.25	5.25	7.25
Fri		3.25	3.25	5.00
Average Congestion %/day	1.42	1.40	1.27	
Average left over inventory %/day	1.74	1.31	1.27	

(c) : Targeted reduction %20

Weekday	Scheme-1	Scheme-2	Scheme-3	
			Clear	Cloudy
Mon	$9.75	11.25	9.75	12.75
Tue		10.50	9.75	12.75
Wed		8.25	8.00	10.50
Thur		11.25	11.25	14.00
Fri		7.50	7.50	10.00
Average Congestion %/day	1.83	1.29	1.17	
Average left over inventory %/day	2.03	1.56	1.44	

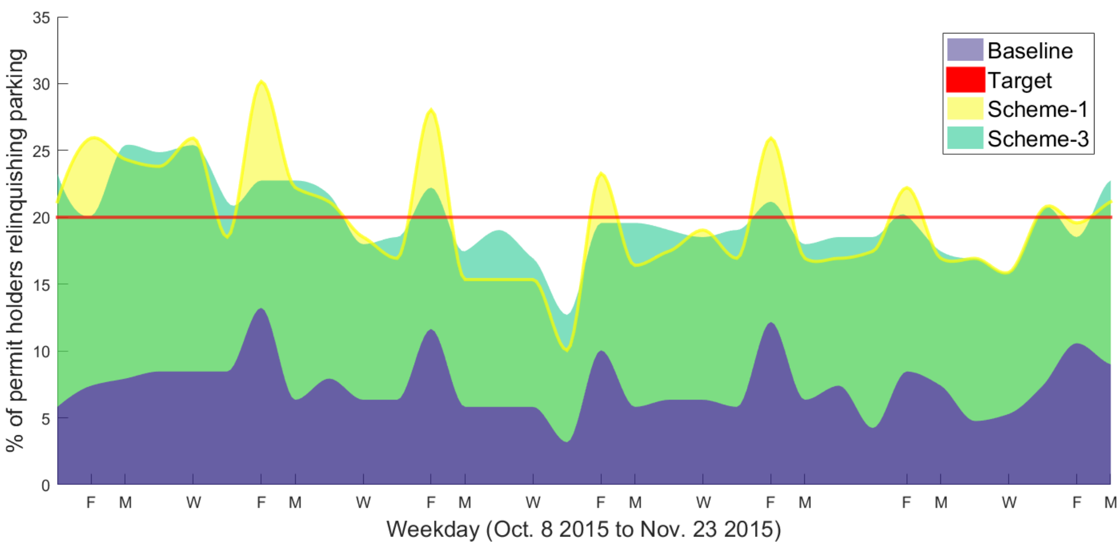


Figure 4.1: Parking demand reduction under Scheme-1 and Scheme-3 during Oct. 8, 2015 to Nov. 23, 2015

Chapter 5

Conclusion

Transportation services, whether as public goods or private commodities, should be priced properly. In this dissertation, we develop two experimental methods for the problem of estimating the price or incentive response curve of a transportation service and apply them to the pricing of employee parking at the UC Berkeley. One method is the randomized controlled trial (RCT), and we use it to measure the change in parking demand caused by a change in price. Our other method is a repeated second-price auction (SPA) used to measure a parking incentive response curve densely.

Our RCT evaluates a daily parking cash-out program, the FlexPass, that un-bundles the university's monthly parking permit. UC Berkeley employees ccan pre-pay for monthly parking by buying a permit with pre-tax dollars. The FlexPass treatment rebates some or all of this amount in proportion to the number of days not parked. The FlexPass study aims to learn if daily rebates can reduce employee parking and measures the number of days parked or not parked by incentiving subjects to report parking each day using an app. The same information was solicited in weekly emails from subjects not using the app. The causal effect of the FlexPass is quantified by estimating and differencing the average number of days parked per subject in the treatment and control groups based on the RCT causation hypothesis.

We apply the box model to the longitudinal parking usage data produced by the app. Potential biases could be generated by underreporting in the control group and dropout in both groups. The underreporting of daily parking consumption is quantified as Missing Not at Random (MNAR) and estimated using the email surveys. We estimate the dropout bias by a sample selection model. We present both the OLS and sample selection models. The sample selection model suggests a smaller treatment effect. We estimate that the FlexPass causes a highly significant reduction of 6.1% in parking consumption (3.40 ± 1.21 days over the 3-month study period). Seventy-seven percent of the subjects reported interest in the incentives a priori. They show a greater and more significant demand reduction. The FlexPass induced a 4.54-day reduction in campus parking per subject within this sub-population.

This is a 0.35-day reduction per week, or an 8.1% demand reduction. Thirteen percent of the subjects own discounted bus passes, which save over 75% of the regular ticket price. This sub-population shows a further demand reduction of 11.24 days during the 3 months. This is a 0.88-day reduction per week, or a 20.6% demand reduction. These reductions required a total rebate of $4,256 to the 158 valid subjects in the treatment group. Each subject received $26.94 on average over the entire study period. The highest rebate for an individual is $285, with most rebates being under $20. We find that unbundling a monthly employee parking permit reduces parking by making employees more mindful of daily parking usage.

We designed the FlexPassPlus experiment to learn parking incentive response curves. This curve is also the cumulative distribution function(CDF) of employees' willingness to accept(WTA) to forgo parking. We generated a direct measurement of this curve by collecting each employee's WTA through a repeated second-price auction in the BDM mechanism. We prove that our variation is incentive compatible, which means employees will bid their true WTA in the auction. By checking the daily bidding results and issuing survey quizzes, we confirmed that the subjects understood the auction rules and revealed their true preference. For instance, subjects whose alternative is to not-commute have a median WTA of $2.25. For those whose alternative is to take transit, the median WTA is $9.50. Since the auction was repeated daily, we were able to measure a separate incentive response curve for each day. We conducted a random effect regression to estimate the average parking incentive elasticity, which is 0.514. The standard deviation for this estimate is 0.005, which is more robust than other estimates in the literature [26, 42, 28].

Confounding variables in before-and-after studies, such as weather condition, become explanatory variables in the FlexPassPlus study. We find that the variations in intensity are due to weekday and weather. In contrast, the elasticity stays rather invariant. When the incentive rate is under $20 per day, the variations in intensity are much higher and dominate the variation of elasticity. The elasticity is significantly higher on cloudy or rainy days (by 0.084) compared to on clear days. The intensity is significantly lower on cloudy or rainy days, by 0.334. We estimated a quantile regression model to extrapolate our sample to the entire population. It models the distribution of an employee's WTA conditioned on her demographics and travel attributes. For example, there is no significant difference in the value of parking for subjects under 54. Subjects 55 to 64 years old have a significantly higher value of parking. Subjects at full-benefit retirement age, 65 or above, value the privilege of campus parking significantly less. We used half the data to estimate the quantile regression and the other half to test it, and we find that the reality should be within the 95% confidence interval of the estimates. The rich information provided by the auction enables both finer parking market segmentation and design of better-targeted incentive schemes. For example, to achieve an average reduction of 20%, we design a fixed-rate cash-out scheme with a $9.75 incentive per day. The same average reduction can be achieved by a variable rate scheme with a $11.25 incentive on Monday, $10.50 on Tuesday, $8.25 on Wednesday, $11.25 on Thursday, and $7.50 on Friday. Since the demand varies at random, on some days the demand exceeds the supply, which results in parking cruising, while on other days the demand is lower than the supply, which results in empty spaces and revenue losses. Given that there are 2,958 permit holders and 2,366 parking spaces (2,958 * 80%), under the fixed-rate scheme, there are, on average, 54 drivers having trouble finding parking per day and 60 spaces left empty per day. Under the variable daily rate scheme we propose, these two numbers would decrease to 38 and 46.

In the future, we will further investigate both the practical and the theoretical potential of our experiments. We conducted a standard RCT with two groups, namely treatment and control. To sample the incentive response cure more densely, instead of the SPA method, we could conduct an RCT with multiple treatment arms, each arm exposed to a different price scheme. That should do away with the auction but would require a much larger sample size to achieve high statistical power. We conducted a reverse SPA to measure the WTA to forgo the campus parking privilege for each day. Our estimate of parking incentive elasticity is different from the SP-survey-based estimates. We would like to conduct more research to explain this difference. After controlling for subjects' demographics, this difference could be due to the assumptions of discrete choice modeling or the hypothetical bias. In the SPA experiment, we observe a subject's WTA and can convert it into a pair of variables, the incentive and its corresponding mode choice. We would then be able to learn a discrete choice model from our synthetic data, and differences in model parameters should reveal the size of the hypothetical bias. The SPA experiment could be conducted at a more detailed level, for example, to measure WTA for each one-hour slot or for different parking locations. We are also interested in designing a location-based parking price scheme for our campus to redistribute the parking demand spatially. In our SPA experiment, we can also build individual-level models based on the WTA data, such as utility indifference curves or individual elasticities. We used the incentive response curve to design daily parking cash-out programs. We can also segment the market by individual preference and design targeted offers for different employees. A crucial problem of implementing price discriminations for ground transportation is that the actual identity of the traveler is hard to obtain. Employee parking, in this case, will be an ideal field, since an employee identification number system usually exists in a corporation.

Appendix A

Proof of Truth Revealing

Table A.1: List of Variables

	Description
i	the incentive ($)
$u : M \times R \to R$	utility function of commuting
A	the set of alternative modes, $a \in A$
$\widetilde{V} : A \to R$	value of parking given a certain alternative mode $a \in A$
W	the value of benefit of forgoing parking
R	the random number generated in our auction. $f(.)$ is its p.d.f.
b	the ask ($)
$\bar{\theta}$	maximal bid
V	value of parking

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$\leq$ $\overline{\theta}$, 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 $[0, \overline{\theta}]$.

Appendix B

FlexPass Study: Recruitment Emails

Recruitment Email

Dear UCB Employee and Parking Permit Holder,

The Department of Parking and Transportation is supporting an research study exploring how mobile and cloud based technology might improve campus parking services. The study will be conducted by UC Berkeley's XMobile Lab and Institute of Transportation Studies, with Professor Raja Sengupta as the Principal Investigator. He would like to invite you to participate in this study. Please read the study details below.

My name is Professor Raja Sengupta. I am a faculty member at UC Berkeley, Civil and Environmental Engineering. I would like to invite you to participate in a research study. You can begin by registering here. Registration should take less than 10 minutes.
If you choose to continue to participate, you will then be invited to test a smartphone App for the Spring semester. This App tests:

- if we can discover parking shortages as they develop, or when you have to drive around looking for parking,
- a smarter parking pricing strategy, and
- learns how you come to campus when not driving.

You will receive a $50 Amazon gift card as a thank you for running the App for the entire study period, i.e, February 1 to April 30, 2015. You may also be randomly selected to earn cash rebates on your parking costs.

Please visit the study website to take the survey and sign up. Space is limited, so sign up today! We hope you will join us in this important research to faciliate and improve campus parking services.

Regards,
Professor Raja Sengupta,
Principal Investigator

Second Round Recruitment Email

Dear UCB Employee and Parking Permit Holder,

If you have not already signed up for the FlexPass study please take a moment to do so at http://xmobile.berkeley.edu/flexpass. You will be requested to install the FlexPass App after taking a short online survey. The survey is estimated to take less than 10 minutes.

Once installed, the App will request your feedback on parking services. We will also try to infer your parking delays from location data collected by the App to reduce the need for your daily input. You will not be required to change your use of parking or pay more.

Also, some of you will be randomly offered rebates for not parking on campus. You can disable the rebate offers if you do not want to change your parking behavior. Your participation is valuable whether you park or not.

This is an academic research study supported by Parking and Transportation. The study is conducted by UC Berkeley's XMobile Lab in collaboration with the Institute of Transportation Studies. The Study Principal Investigator is Professor Raja Sengupta. The study tests mobile technology for the improvement of campus parking services.

Don't delay. Registration closes Sunday, January 25. See http://xmobile.berkeley.edu/flexpass for more info about this research study.

Thank you!

Lauren Bennett
Travel Demand Manager
Parking & Transportation
University of California, Berkeley

Appendix C

FlexPass Study: Informed Consent

The UCB FlexPass Study

Introduction and Purpose

This experiment is designed to collect information for a research study at the University of California, Berkeley. The study is being led by Prof. Raja Sengupta (PI) and his research group, henceforth referred as the lead investigators. The goal of the study is to test mobile technology for greener and better service to campus parking permit holders. We will use this information to understand if we can discover parking shortages quickly with help from our permit holders' smartphones, detect who is being forced to drive around looking for parking and make recommendations for pricing changes that improve parking availability and contribute to a greener campus.

Procedures

You are only allowed to take part in this study if you are 18 or older and are a 'C' or 'F' permit holder. As a first step in the study, you will be asked to respond to a few demographic, mobile technology and commute related questions about yourself. Then you will be requested to install a smartphone App and keep it running for the study period. If you agree, you will directed to create an account for the study. This process, including creating a new account for the study, if you chose to do so, should take about 10 to 15 minutes to complete. Using the employee ID that you shall provide during the registration, we will access your record in the Parking and Transportation database and automatically retrieve your first and last name, current permit number and the registered email address with P&T.

Next you will be sent an email with an activation link and other study related information. After account activation, you will be requested to download and install the FlexPass App designed for your phone. The FlexPass app will store and periodically upload the self-reported commute history. *Location data* will be collected in the background to detect parking demand and infer daily activity-travel patterns*. In view of this, we request you to keep your location data enabled.* As part of the study, your *phone location (tracking/GPS) data, IP addresses, phone IMEI numbers, email addresses and employee ids, henceforth referred to as Personally Identifiable Information (PII).* Your location data will be collected continuously at all hours. You can disable location access to stop this. The "Confidentiality" section below explains how this information will be protected and what will be retained after the study.

As a participant in the study, you will be randomly assigned either to the *'control'* or *'treatment'* group (the system assigns participants through a random process that is similar to something like a flip of a coin). If assigned to the *control* group, you will only be required to install the FlexPass App and run it for the entire study period as described above. You will keep your current permit. If assigned to the *treatment* group, you will be asked to turn in your current hang-tag and receive an alternate one for the study period. You can make this exchange at the P&T office. If you are unable to go to the office please contact us as soon as possible to make alternative arrangements before the study begins. The study will run for 3 months beginning on February 1, 2015 and ending on April 30, 2015.

Starting from the time of installation of the application, you will be allowed to report whether or not you will park on campus each day. If you indicate that you will not park, you will also be asked to report what alternate mode you would be taking or whether you would not be coming to campus. This process should take no more than 10 seconds per instance. If you haven't changed the default mode for a future day *at least once by the previous evening at 6pm*, you will receive a notification on your phone reminding you to do so. This notification will play the default sound on your phone for notifications and can be ignored. You can also turn off the notifications.

Your responses regarding whether or not parking on a certain day will be uploaded to the server through the FlexPass App and then sent to parking enforcement officers. As part of the *treatment* group, if you indicate that you are not going to park, you will be allotted a rebate for that day based on your pricing structure (see below under compensation) but you are then not allowed to park on campus that day. If you do, you might potentially receive a parking citation/ticket. The default mode for every day will be "Parked on Campus". You can change your commute choice for a certain day in the study period, multiple times but only till 12:30pm on that day. Since this is a long-term, longitudinal study, we will continue to collect data as long as the application is installed.

At the end of the study, we will send you a link to an online exit survey that we ask you to please fill out. That survey should take at most 10 minutes to complete.

Benefits

You might be able to reduce your cost of on-campus parking during the time when you are enrolled in the study. Based on the data we collect from the study, we will recommend structural changes to the UC Berkeley campus parking permit system and suggest incentives for more energy and cost efficient campus parking. In the long run, your participation will help reduce congestion on UC Berkeley's parking lots and reduce your and the campus' carbon footprint without affecting work schedules.

Risks and Discomforts

The biggest concern that we expect is the battery drain on the phone, which is comparable to any typical app that collects location data in the background. Furthermore, as part of *treatment* group if you indicate that you will not park on campus and your vehicle is found on a campus parking lot on that particular day, you risk receiving a citation from Parking and Transportation. Also, depending on your data plan, you may incur additional charges for data transmission from your phone.

As with all research, there is a risk of invasion of privacy if your tracking data and/or survey data were to be exposed to a third party. The data may allow a third party to identify your home and work location, your trip history during the study period and your email address and employee id as contained in the signup data. We will be using the best practices to avoid this risk as described in the "Confidentiality" section.

Lastly, there is a potential risk of accident if you were to react to a notification by your cell phone when it is not safe to do so (e.g. while driving or operating machinery).

Confidentiality

Your email addresses and employee id numbers will be accessible to the lead researchers and Parking and Transportation to access your parking records during the study and issue refunds at the end of the study. We understand that location data and other PII can be sensitive and we have taken several precautions related to the security of your data provided. In particular:

1. All communication between our websites, our apps and our server is encrypted.
2. We divide our server endpoints that communicate with the app into ones that expose PII and your personal data, such as your personal rebates, and ones that expose aggregate information, such as the average rebates of all UC Berkeley participants. All endpoints require authentication before exposing PII.
3. We use your email address registered with P&T and provided password for authentication. To avoid risks we request you to create a separate password just for this study.
4. The trip, phone and demographic data is associated with unique anonymous user IDs and not with the email addresses. The mapping from the user IDs to the email addresses is done through a separate table. Only the lead researchers have database access to both trip and user data including the PII. Other researchers will only have access to data from trips, exported by the lead researchers without the associated user data and PII.
5. The server executing the web application including the sign up and initial survey is hosted in the Berkeley IST Cloud and is protected according to the university's data security standards. It is protected by a firewall, which only exposes the ports Secure Shell (SSH) and Web Server (HTTPS). The database cannot be accessed directly from outside the server. SSH access to the server is configured to only support public key authentication, and the only users with access to the server private key are the lead researchers.

The exit survey is conducted using Qualtrics. Qualtrics uses HTTPS for all transmitted data. The data is hosted by third party data centers that are SSAE-16 SOC II certified. All data at rest are encrypted, and data on deprecated hard drives are destroyed by U.S. DOD methods and delivered to a third-party data destruction service.

At the end of the study, we will destroy the table linking email addresses and other PII with the user ID. The trip-table containing user IDs along with the list of trips and demographic information will be retained as a travel pattern dataset for ongoing research. Both the initial and exit survey data is also connected only with the non-personally identifying user IDs. The travel pattern dataset and survey data will be retained indefinitely and shall available for future research to external researchers only by written request to the PI. They will have to agree that they will publish only aggregate, non-personally identifiable results, and that they will not re-share the data with others. The dataset will not be used for any marketing or advertising purposes.

Compensation

There will be a guaranteed $50 Amazon gift card just for participating and running the FlexPass App for the entire study period. If you are assigned to the *treatment* group, you will receive an additional rebate based on your permit type and the number of working days (Mon to Fri) you park on campus in a given month. Based on the number of working days driven to campus and your permit type, the rebate amount is outlined below.

For example, as an F permit holder, if you park 12 workdays (approximately 3 work days a week), you will receive a rebate of $23, if you park 13 days, you will receive a rebate of $17 (i.e. $23-$6) and so on till a maximum of $95 for a month. Since you will have already prepaid for your permit parking, the entire credit for three months will be refunded to you as a lump sum at the end of the study.

# of working days parked this month on-campus	C Permit Rebate for the month	F Permit Rebate for the month
0	$131	$95
1	$123	$89
2	$115	$83
3	$107	$77
4	$99	$71
5	$91	$65
6	$83	$59
7	$75	$53
8	$67	$47
9	$59	$41
10	$51	$35
11	$43	$29
12	$35	$23
13	$27	$17
14	$19	$11
15	$11	$5
16	$3	$0
≥17	$0	$0

Rights

Participation in research is completely voluntary. You have the right to decline to participate or to withdraw at any point in this study without penalty or loss of benefits to which you are otherwise entitled. If you choose to withdraw from this study, you will receive any parking credits that you have earned up to that point only if you are part of the *treatment* group. However, for both *control* and *treatment* groups, you will not receive your gift card if you withdraw before the end of study on April 30, 2015. If you want to remain in the study but do not want us to collect your location data, you can turn off location services on your phone. In order to withdraw permanently, you can uninstall the app. In addition, please email the lead researchers at flexpasshelp@berkeley.edu to inform them of your withdrawal.

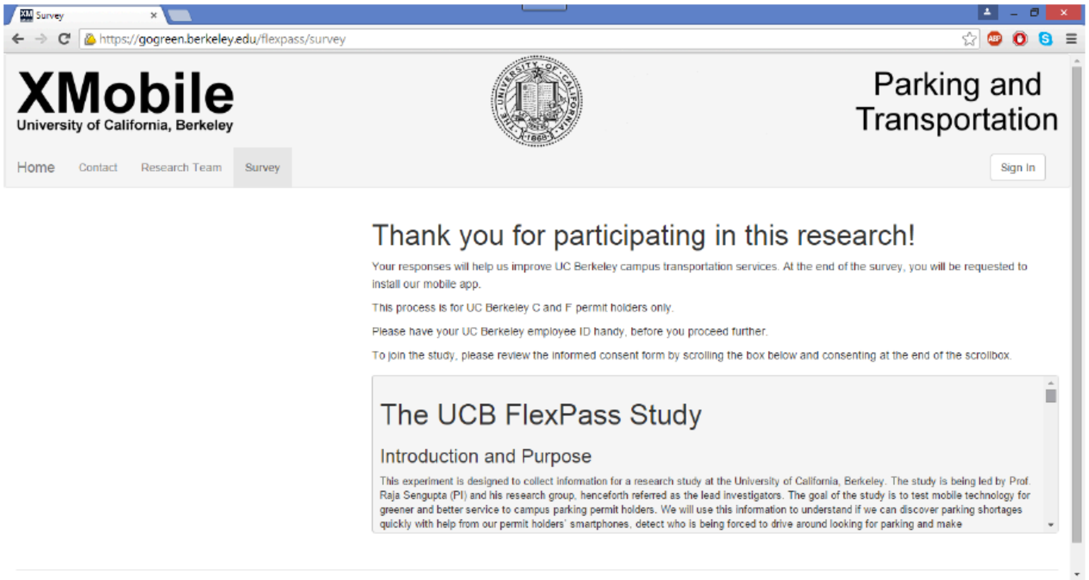
Questions

If you have any questions about this research, please feel free to contact us. For the quickest response, you can send an email to flexpasshelp@berkeley.edu with the appropriate subject. If you want to contact only the PI, you can contact him at rajasengupta@berkeley.edu. If you have any questions about your rights or treatment as a research participant in this study, please contact the University of California at Berkeley's Committee for Protection of Human Subjects at 510-642-7461, or email subjects@berkeley.edu. If you agree to participate in this research, please click on "I consent to taking part in this research", and please print a copy of this page for future reference. If you do not wish to take part, please quit the registration process. This notice is also available online after you register in case you need to read it again in the future.

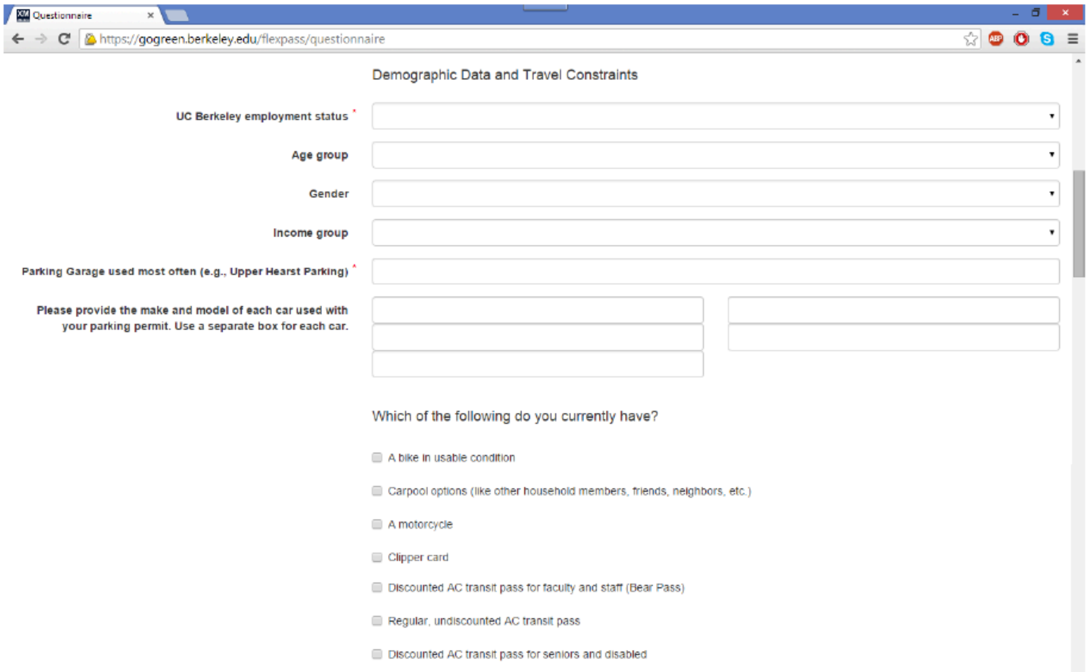
Appendix D

FlexPass Study: Registration Website and Entry Survey

Step 1: Questionnaire/Initial survey consent part:



Step 1: Initial Survey after scrolling and checking "I consent…" above (part 1)


Questionnaire

https://gogreen.berkeley.edu/flexpass/questionnaire

Demographic Data and Travel Constraints

UC Berkeley employment status *

Age group

Gender

Income group

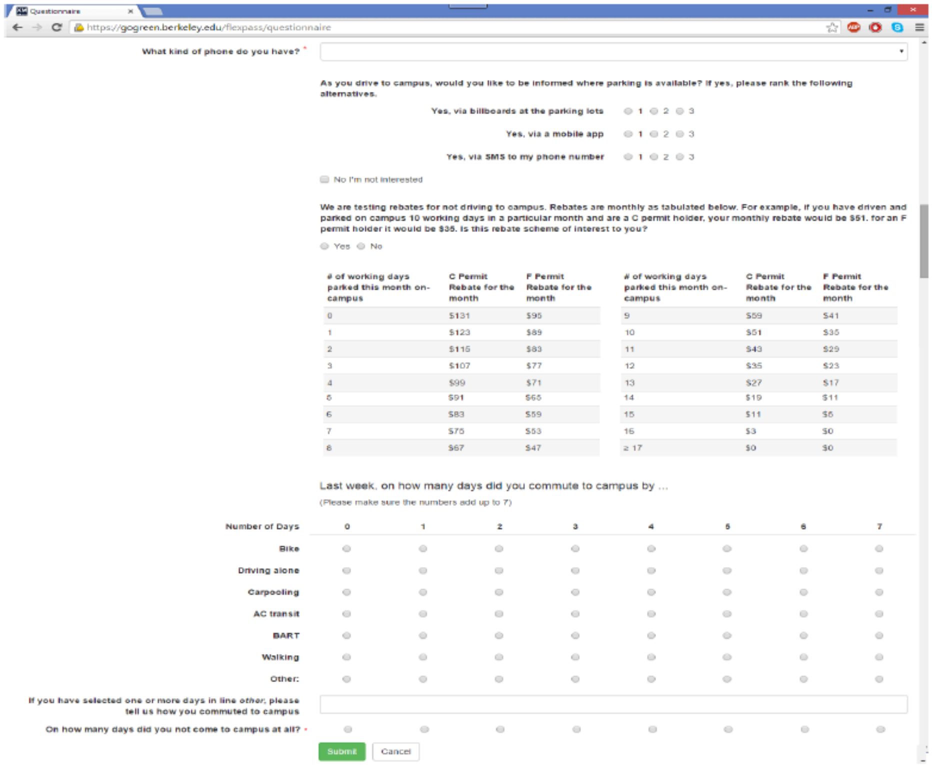
Parking Garage used most often (e.g., Upper Hearst Parking) *

Please provide the make and model of each car used with your parking permit. Use a separate box for each car.

Which of the following do you currently have?

- A bike in usable condition
- Carpool options (like other household members, friends, neighbors, etc.)
- A motorcycle
- Clipper card
- Discounted AC transit pass for faculty and staff (Bear Pass)
- Regular, undiscounted AC transit pass
- Discounted AC transit pass for seniors and disabled

Step 1: Initial Survey (part 2)



Questionnaire

https://gogreen.berkeley.edu/flexpass/questionnaire

What kind of phone do you have? *

As you drive to campus, would you like to be informed where parking is available? If yes, please rank the following alternatives.

Yes, via billboards at the parking lots 1 2 3

Yes, via a mobile app 1 2 3

Yes, via SMS to my phone number 1 2 3

No I'm not interested

We are testing rebates for not driving to campus. Rebates are monthly as tabulated below. For example, if you have driven and parked on campus 10 working days in a particular month and are a C permit holder, your monthly rebate would be $51. for an F permit holder it would be $35. Is this rebate scheme of interest to you?

Yes No

# of working days parked this month on-campus	C Permit Rebate for the month	F Permit Rebate for the month	# of working days parked this month on-campus	C Permit Rebate for the month	F Permit Rebate for the month
0	$131	$95	9	$59	$41
1	$123	$89	10	$51	$35
2	$115	$83	11	$43	$29
3	$107	$77	12	$35	$23
4	$99	$71	13	$27	$17
5	$91	$65	14	$19	$11
6	$83	$59	15	$11	$5
7	$75	$53	16	$3	$0
8	$67	$47	≥ 17	$0	$0

Last week, on how many days did you commute to campus by ...

(Please make sure the numbers add up to 7)

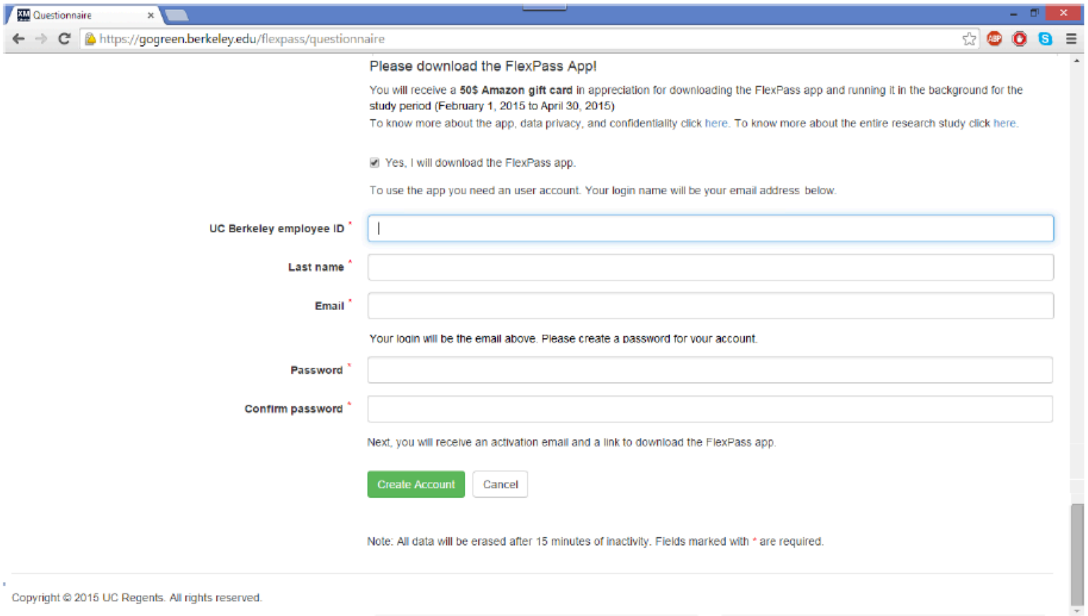
Number of Days	0	1	2	3	4	5	6	7
Bike								
Driving alone								
Carpooling								
AC transit								
BART								
Walking								
Other:								

If you have selected one or more days in line *other*, please tell us how you commuted to campus

On how many days did you not come to campus at all? *

Submit Cancel

Step 2: After submitting above the participant may choose to proceed further to participate by installing the app that needs to be run for the study period to receive the gift card. The account creation is displayed after selecting the check box.



Appendix E

FlexPass Study: Emails to the Treatment Group and Control Group

Email to the Rebate group:

Sub: Flex Pass Study - Assignment for the Randomized Controlled Trial

Thank you for participating in the FlexPass study! You are eligible for rebates. This means you can claim cash rebates on your daily parking charges for the days you do not park in campus. See our study website for more detail on how this works (after signing in our system).

Action Item: We need to exchange your current parking permit for the study permit, the FlexPass. Please visit the Parking and Transportation office during one of the scheduled times below to make the exchange.

Tuesday Jan 27	Wednesday Jan 28	Thursday Jan 29
8:30am-12pm	8:30am-12pm	8:30am-12pm

P&T office is located at 2150 Kittredge, 1st floor lobby. [map]

For questions, please email flexpasshelp@berkeley.edu or call 510-859-4445

On completion of the study, your original parking permit will be returned to you

Email to the control group:

Thank you for participating in the FlexPass study! You have been randomly selected for the Control Group. This means you are NOT eligible to receive cash rebates on your daily parking charges for the days you do not park in campus.

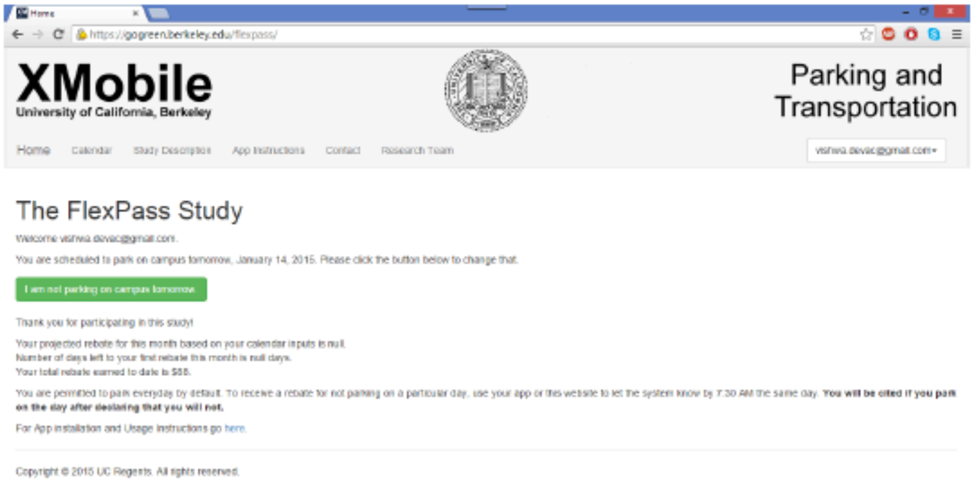
Action Item: We ask that you download the FlexPass app (if you haven't already) and keep it running until the end of the study, May 1, 2015. If you run the app throughout the study period, we will email you a $50 Amazon giftcard. The Control Group is very important for the outcome of the study. Thank you for your participation. Your input will help improve campus parking!

For questions, please email flexpasshelp@berkeley.edu or call 510-859-4445

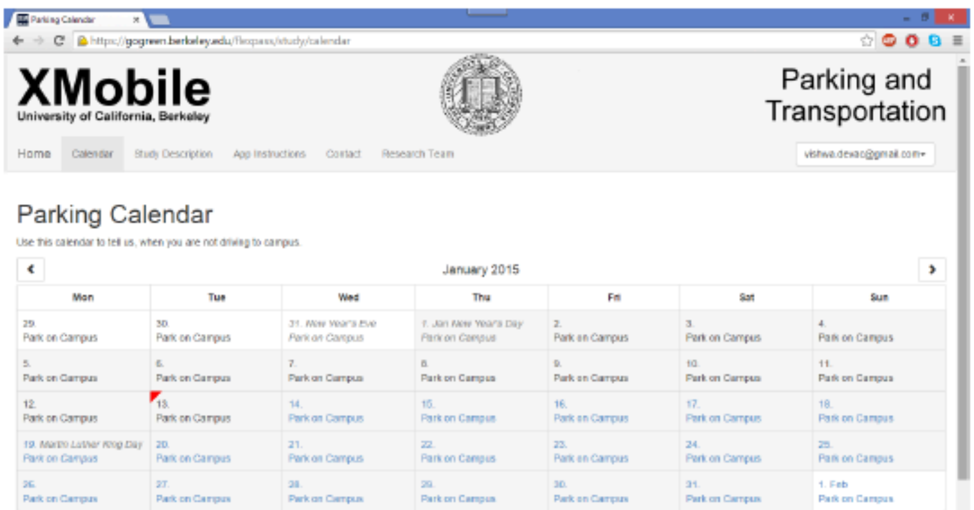
Appendix F

FlexPass Study: App Design and Screen Shots

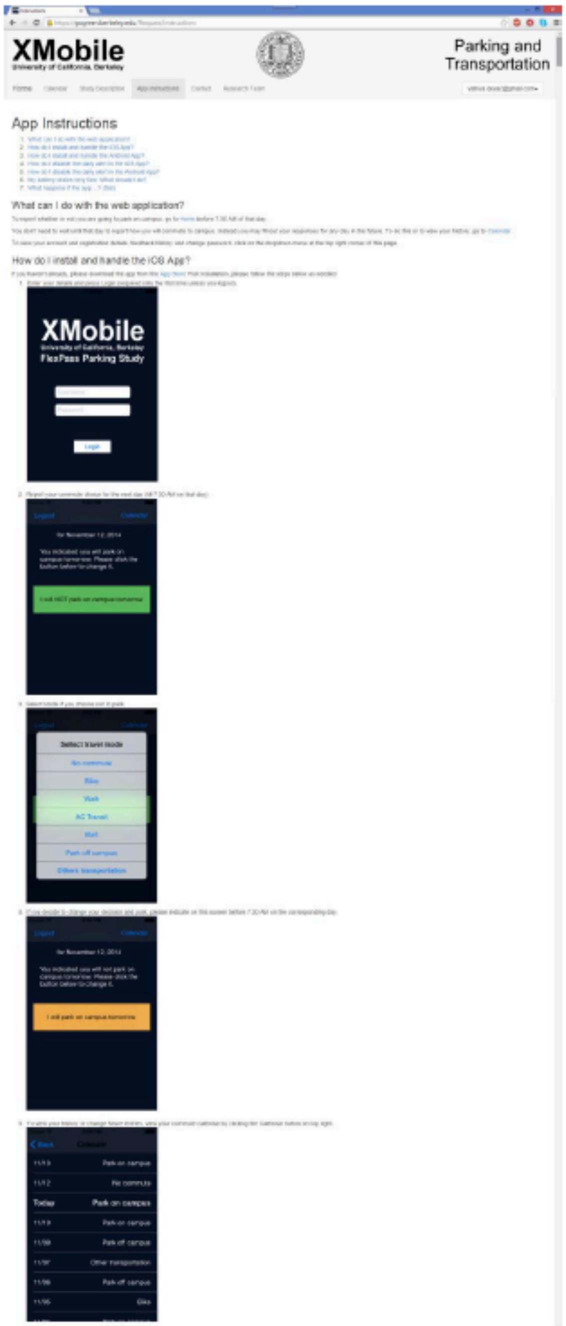
Home page :

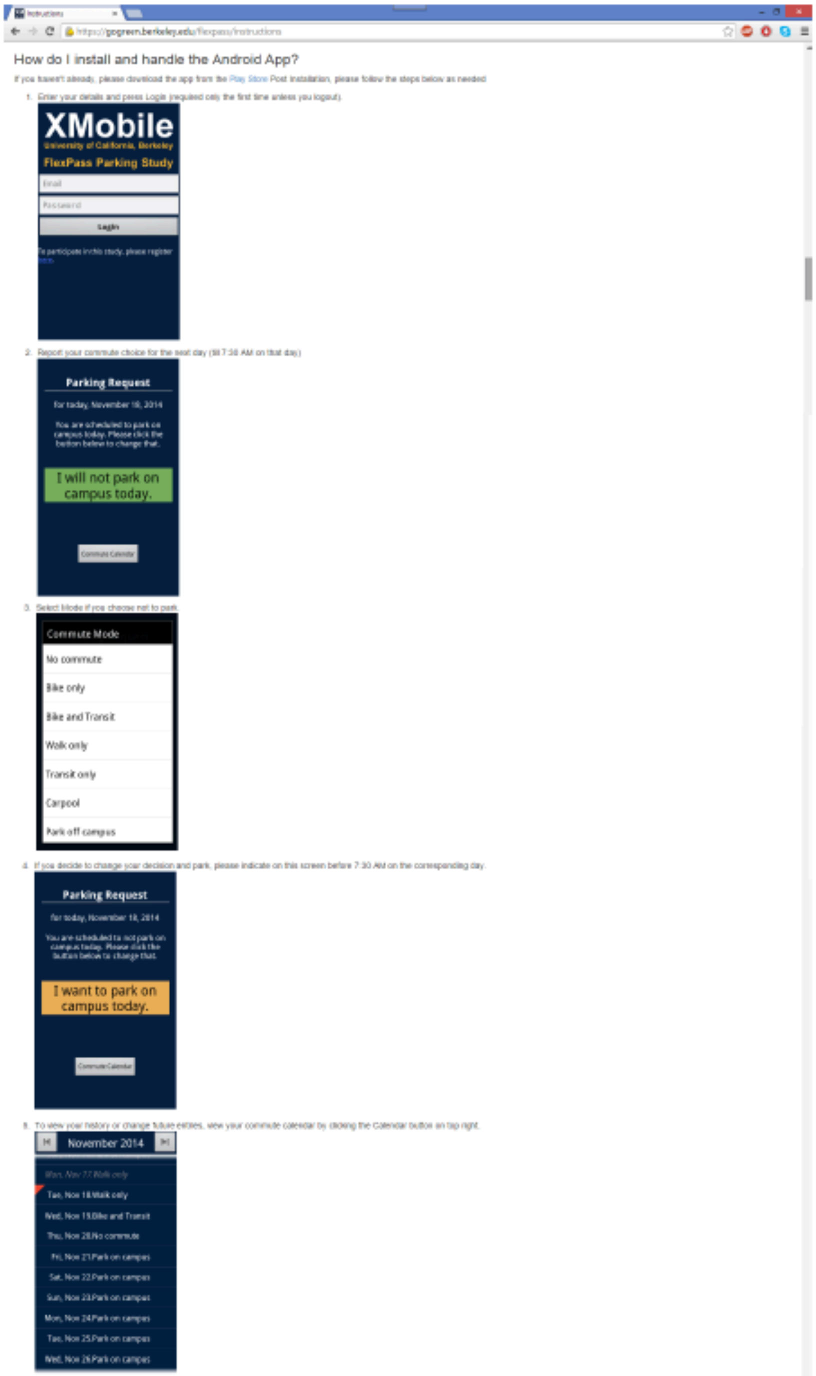


Parking Calendar:



Instructions Pages:




How do I install and handle the Android App?
XMobile
FlexPass Parking Study
Parking Request
I will not park on campus today.
Commute Mode
No commute
Bike only
Bike and Transit
Walk only
Transit only
Carpool
Park off campus
Parking Request
I want to park on campus today.
November 2014

Appendix G

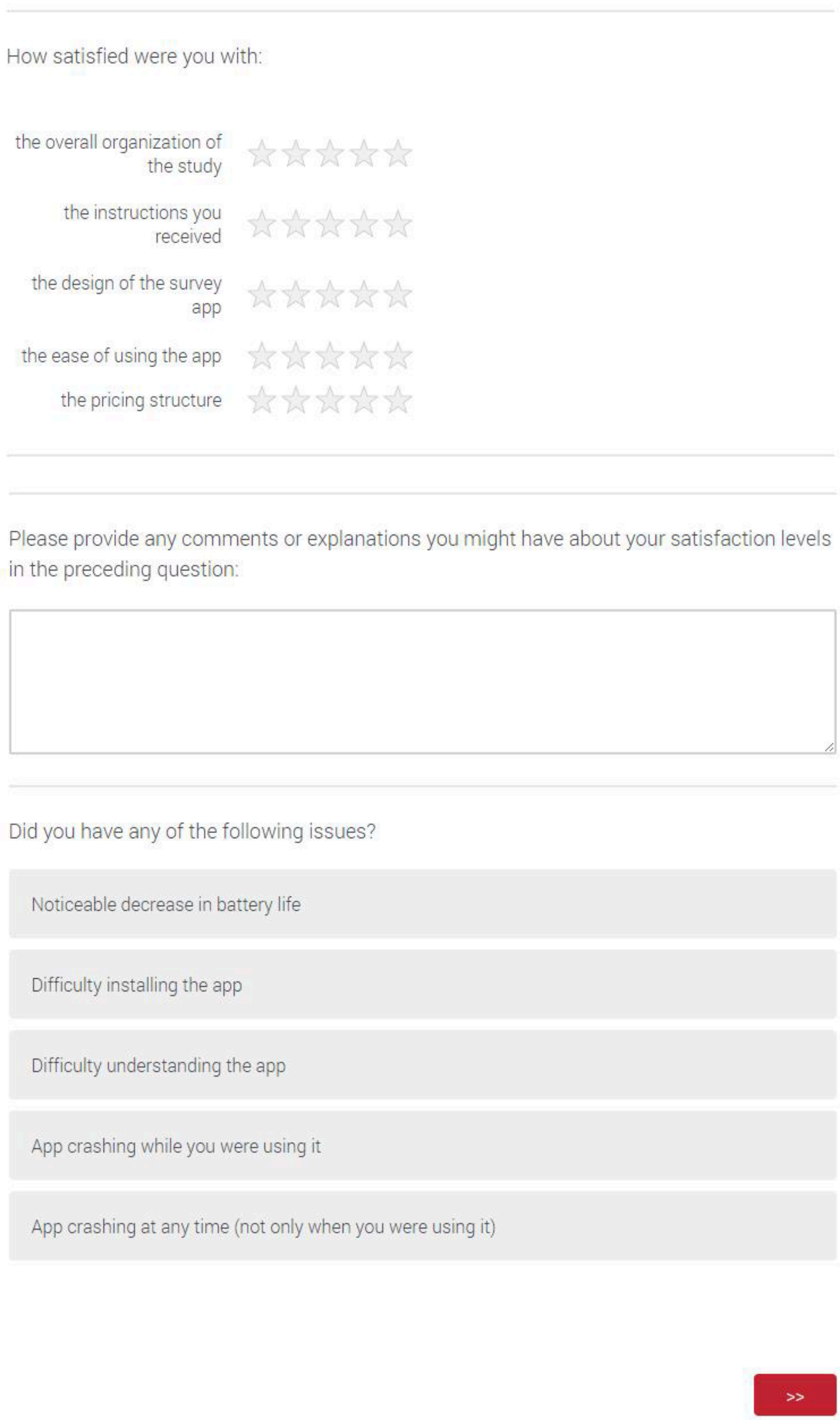
FlexPass Study: Exit Survey

Exit Survey page 1:

Thank you very much for taking the time to fill out this survey! We appreciate your feedback.

What was your main motivation for taking part in this study?

- Reducing your carbon footprint
- Exploring alternative commute options
- Saving money on parking
- Supporting research
- Other:



How satisfied were you with:

the overall organization of the study	☆☆☆☆☆
the instructions you received	☆☆☆☆☆
the design of the survey app	☆☆☆☆☆
the ease of using the app	☆☆☆☆☆
the pricing structure	☆☆☆☆☆

Please provide any comments or explanations you might have about your satisfaction levels in the preceding question:

Did you have any of the following issues?

Noticeable decrease in battery life

Difficulty installing the app

Difficulty understanding the app

App crashing while you were using it

App crashing at any time (not only when you were using it)

>>

Exit survey page 2:

What did you do in response to the problems?

- Nothing
- Reinstall the app during the study
- Completely remove the app before the end of the study
- Emailed flexpasshelp@berkeley.edu or called 510 697 2417; problem was resolved
- Emailed flexpasshelp@berkeley.edu or called 510 697 2417; problem was not resolved
- Other:

Do you have any other comments regarding the study?

<< >>

Appendix H

FlexPassPlus Study: Recruitment Emails

Recruitment Email

Dear UCB Employee and Parking Permit Holder,

The Department of Parking & Transportation, invites you to participate in an academic research study, FlexPass Plus, conducted by UC Berkeley's XMobile Lab and the Institute of Transportation Studies. As the university grows, putting parking under increasing pressure, we must innovate to maintain our quality of service.

FlexPass Plus continues the successful FlexPass study conducted in Spring 2015 with 400 of our employee permit holders. This latest study offers participants the opportunity to earn rebates for not parking on campus plus the opportunity to set the price of the rebate. It's simple and quick to participate. Here's how:

- Participate when you do not want to park on campus for a given working day (weekends and holidays excluded).
- On that day, use the app to set your price for not parking on campus.
- Know you have to park on campus? No need to open the app that day.

If your rebate price is accepted, you earn the rebate and you will NOT be able to use your permit to park on campus that day ONLY. All of the rebates you earn during the study will be issued to you via payroll in December.

The study involves:
- Installing the FlexPass Plus App on your smartphone and keeping it running for the study period, i.e., September 1 to November 30, 2015. You are not required to use it.
- Completing our entry and exit surveys. This will require 10 minutes or less in August and once again in December. This is very valuable to the research. As appreciation for participation in the study, you will receive two $25 Amazon gift cards, one for completing the entry survey and another for running the app and completing the exit survey.

Please visit the study website for more information and to take the survey and sign up. Space is limited, so sign up today! Registration closes August 28. We hope you will join us in this very important campus initiative.

Regards,
Raja Sengupta
Principal Investigator
Institute of Transportation Studies

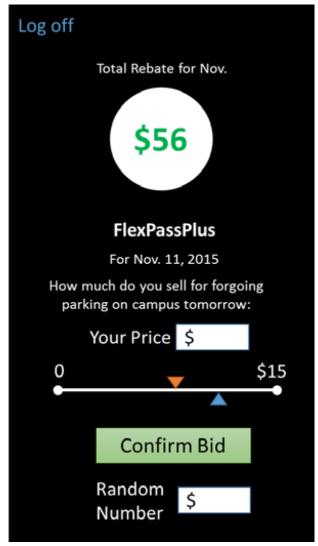
Lauren Bennett
Campus Transportation Demand Manager
Parking & Transportation

Appendix I

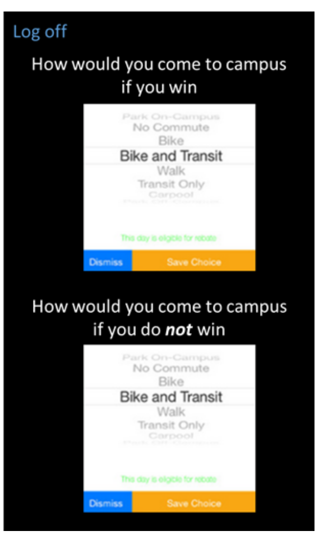
FlexPassPlus Study: App Design and Screen Shots

1. Sign in screen

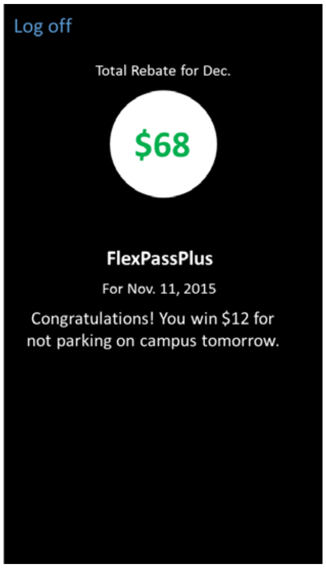
2. Screen before participants bid



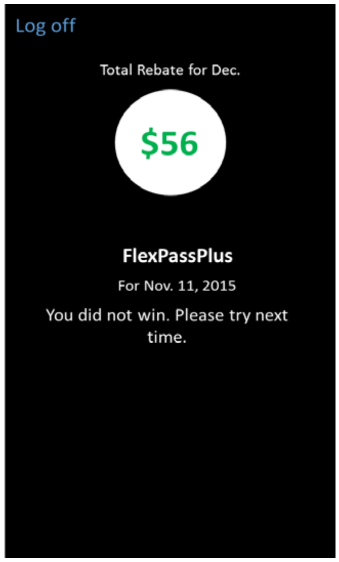
4. Screen after participants confirm bid



4. Screen if participants win the action



5. Screen if participants did not win the auction



6. Calendar view of auction history

Appendix J

FlexPassPlus Study: Informed Consent

The UCB FlexPass Plus Study

Introduction and Purpose

This experiment is designed to collect information for a research study at the University of California, Berkeley. The study is being led by Prof. Raja Sengupta (PI) and his research group, henceforth referred to as the lead investigators. The goal of the study is to understand parking behavior, especially employees' willingness to forgo parking on campus, and employee commute mode choice to campus. We will use this information to make recommendations for pricing changes that improve parking availability and contribute to a greener campus.

Procedures

You are only allowed to take part in this study if you are 18 years of age or older and are a 'C' or 'F' permit holder. As a first step in the study, you will be asked to respond to a few demographic, mobile technologies and commute related questions about yourself. Then you will be requested to install a smartphone App and keep it running for the study period. If you agree, you will be directed to create an account for the study. This process, including creating a new account, if you choose to do so, should take about 10 to 15 minutes to complete. Using your employee ID, we will access your record in the Parking and Transportation database and automatically retrieve your first and last name, current permit number and the registered email address with Parking and Transportation (P&T).

Next you will be sent an email with an activation link and other study related information. After account activation, you will be requested to download and install the FlexPass Plus app for your phone. If you were a participant in the previous FlexPass study, you will not be required to create a new account, complete the initial survey or re-activate your existing account. You will just be required to update your current FlexPass App to the new FlexPass Plus App and provide consent to this document before using the new App. The FlexPass Plus app will store and periodically upload daily parking activity including confirmed parking sales and the self-reported commute history. *Location data* will be collected in the background to detect parking demand and infer daily activity-travel patterns. *In view of this, we request you to keep your location data enabled.* As part of the study, your *phone location (tracking/GPS) data, IP addresses, phone IMEI numbers, email addresses and employee ids, henceforth referred to as Personally Identifiable Information (PII)* will be collected at all hours. You can disable location access to stop this. The "Confidentiality" section below explains how this information will be protected and what will be retained after the study.

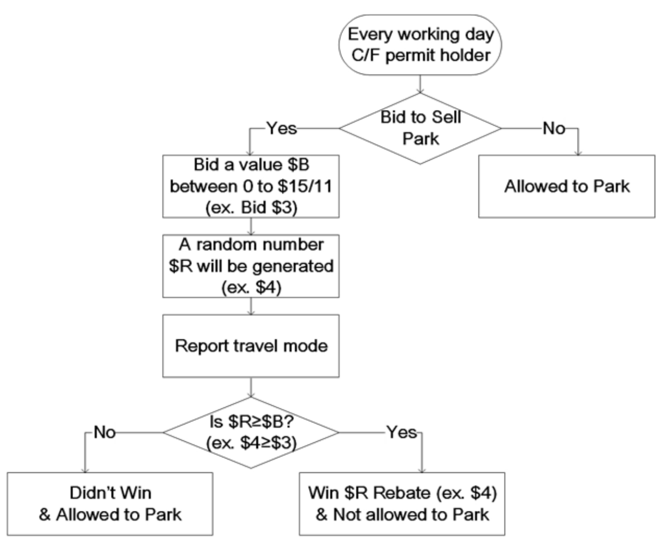
The study will begin on September 1, 2015 and end on November 30, 2015. The two dates define the study period.

CPHS# 2014-09-6722

Upon installation of the application, you will have the opportunity to sell your parking on campus each working day (Mon. to Fri.) during the study period. As an F permit holder you can ask to be paid any amount up to $11 to sell your parking on campus for the day. As a C permit holder you can bid any amount up to $15. After you submit your price, the App will pick a random amount as market price, uniformly generated, between $0 and the maximum amount you can ask for, i.e. $11 or $15. If the random amount is greater than or equal to your bid, you win and your bid is accepted at the random market price. The research team will credit that random amount to your account and you will *not* be able to use your permit to park on campus that day. If the random number is less than your bid or you did not participate for the day, you are allowed to park on campus. The App will also prompt you to report the mode you will use to get to campus or not coming at all.

The random amount picked as market price is generated by the App software from a uniform distribution. All such amounts in your range ($0-$11 or $0-$15) have an equal probability of being generated. i.e. they are entirely random. However, the probability of you winning the bid will depend on the amount you bid.

For example, if you are a C 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 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 place your bid at your true willingness to accept compensation to forgo parking. For example, it may cost you $10 to take transit (say $5 for ticket and $5 for time cost). Then submitting your price at $10 maximizes your net benefit. The following chart illustrates the procedure for selling your parking access and possible outcomes.



CPHS# 2014-09-6722

Your responses regarding whether or not you are parking on a given day will be uploaded to the server through the FlexPass Plus app and sent to parking enforcement officers. If you sell your parking access, but park on campus, you will potentially receive a parking citation. Once you submit your bid for a given day, you cannot change it or participate again. You can bid on the following day beginning at 12:01pm. . If you haven't bid for a future day *at least once by the previous evening at 6pm*, you will receive a notification on your phone reminding you to do so. Since this is a long-term, longitudinal study, we will continue to collect data as long as the application is installed.

At the end of the study, you will receive an email with a link to the exit survey. The survey should take no more than 10 minutes to complete.

Benefits

You can potentially reduce your cost of on-campus parking during the time you are enrolled in the study. Based on the data we collect from the study, we will recommend structural changes to the UC Berkeley campus parking permit system and suggest strategies to improve campus parking. Your participation will produce valuable insights to create programs that ease the burden of campus parking.

Risks and Discomforts

The biggest concern that we anticipate is battery drain on the phone, which is comparable to any typical app that collects location data in the background. Furthermore, if you sell your parking access on a given day and your vehicle is found on a campus parking lot that day, you risk receiving a citation from Parking and Transportation. Also, depending on your data plan, you may incur additional charges for data transmission from your phone.

As with all research, there is a risk of invasion of privacy if your tracking data and/or survey data were to be exposed to a third party. The data may allow a third party to identify your home and work location, your trip history during the study period and your email address and employee id as contained in the signup data. We will be using best practices to avoid this risk as described in the "Confidentiality" section.

Lastly, there is a potential risk of accident if you were to react to a notification by your cell phone when it is not safe to do so (e.g. while driving or operating machinery).

Confidentiality

Your email address and employee id number will be accessible to the lead researchers and Parking and Transportation in order to access your parking records during the study and issue refunds at the end of the study. We understand that location data and other PII can be sensitive and we have taken several precautions related to the security of your data. In particular:

1. All communication between our websites, our apps and our server is encrypted.

2. We divide our server endpoints that communicate with the app into ones that expose PII and your personal data, such as your personal rebates, and ones that expose aggregate information, such as the average rebates of all UC Berkeley participants. All endpoints require authentication before exposing PII.

3. We use the email address registered with P&T and provided password for authentication. To avoid risks we request that you create a separate password just for this study.

4. Trip, phone and demographic data is associated with unique anonymous user IDs and not with the email address. Mapping from the user IDs to the email address is done through a separate table. Only the lead researchers have database access to both trip and user data including the PII. Other researchers will only have access to data from trips, exported by the lead researchers without the associated user data and PII.

5. The server executing the web application including the sign up and initial survey is hosted in the Berkeley IST Cloud and is protected according to the university's data security standards. It is protected by a firewall, which only exposes the ports Secure Shell (SSH) and Web Server (HTTPS). The database cannot be accessed directly from outside the server. SSH access to the server is configured to only support public key authentication, and the only users with access to the server private key are the lead researchers.

The exit survey is conducted using Qualtrics. Qualtrics uses HTTPS for all transmitted data. The data is hosted by third party data centers that are SSAE-16 SOC II certified. All data at rest are encrypted, and data on deprecated hard drives are destroyed by U.S. DOD methods and delivered to a third-party data destruction service.

If you had participated in the previous study, you will not be asked to complete the initial survey again but we will continue to use your identifiable information throughout this study. The identifiable information collected for all participants in the FlexPass Plus study will be destroyed in December 2016.

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At the end of the study, we will destroy the table linking email addresses and other PII with the user ID. The trip-table containing user IDs along with the list of trips and demographic information will be retained as a travel pattern dataset for ongoing research. Both the initial and exit survey data is also connected only with the non-personally identifying user IDs. The travel pattern dataset and survey data will be retained indefinitely and shall available for future research to external researchers only by written request to the PI. They will have to agree that they will publish only aggregate, non-personally identifiable results, and that they will not re-share the data with others. The dataset will not be used for any marketing or advertising purposes.

Compensation

You will receive one $25 Amazon gift card for completing the registration survey and one $25 Amazon gift card for completing the exit survey. If you took part in the FlexPass study in the Spring of 2015 and completed the entry survey, you do not have to complete it again and are not eligible for the first $25 Amazon gift card. You will receive an additional rebate based on your permit type and the auction results of working days (Mon to Fri) in a given month. If you are an F permit holder you will be able to receive at most $98 for each month in the study period. If you are a C permit holder will be able to receive at most $137 for each month in the study period.

Rights

Participation in research is completely voluntary. You have the right to decline to participate or to withdraw at any point in this study without penalty or loss of benefits to which you are otherwise entitled. If you choose to withdraw from this study, you will receive any parking credits that you have earned up to that point. However, you will not receive your second $25 gift card (meant for running the App throughout the study and completing the exit survey), if you withdraw before the end of study on November 30, 2015. If you want to remain in the study but do not want us to collect your location data, you can turn off location services on your phone. In order to withdraw permanently, you can uninstall the app. In addition, please email the lead researchers at flexpasshelp@berkeley.edu to inform them of your withdrawal.

Questions

If you have any questions about this research, please feel free to contact us. For the quickest response, you can send an email to flexpasshelp@berkeley.edu with the appropriate subject. If you want to contact only the PI, you can contact him at rajasengupta@berkeley.edu. If you have any questions about your rights or treatment as a research participant in this study, please contact the University of California at Berkeley's Committee for Protection of Human Subjects at 510-642-7461, or email subjects@berkeley.edu. If you agree to participate in this research, please click on "I consent to taking part in this research", and please print a copy of this page for future reference. If you do not wish to take part, please quit the registration process. This notice is also available online after you register in case you need to read it again in the future.

CPHS# 2014-09-6722

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