# A Casual Analysis of FlexPass: Incentives for Reducing Parking Demand

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**ABSTRACT (221 WORDS)**

A parking incentive program named FlexPass have been conducted in University of California, Berkley. The causal structure underlying employee parking behavior is examined in this study by a randomized controlled trial, where participants receiving treatment were offered incentives for parking less and taking other modes. This field experiment lasted for three months and recruited 392 staff and faculty members. Practicable problems encountered during the study were non-random differential dropout after the group assignment and non-ignorable missing data. Missing data were measured by follow-up emails and estimated utilizing a mixed latent factor model, which outperformed traditional feature based models. Dropout bias was corrected by sample selection model. During the study, control participants, served as baseline, parked 4.3 days per week and the FlexPass induced an average treatment effect of 4.2% parking demand reduction. A heterogeneity treatment effect has been discovered. Participants who claimed to be interested in the pricing scheme, accounted for 77% of the enrolled population. There is a larger treatment effect of 6.0% in this group. For the rest, most of whom are regular drives, there is no significant treatment effect. The finding suggests that instead of building new parking structures, increasing the parking prices and providing incentives at the same time could reduce parking demand. It also brings significant rewards to those who choose to travel by other modes.



**KEYWORD**: Transportation Demand Management; Incentives Parking; Randomized Controlled Trial; Casual Inference

## INTRODUCTION

In order to reduce on-campus parking demand and create a more sustainable environment, a new parking pricing strategy is being proposed by the Parking and Transportation office of University of California, Berkeley (P&T of UC Berkeley). This parking pricing strategy, named FlexPass, is to be priced to provide an incentive to park less on working days, and preferably less than four working days per week. Before formally launching the FlexPass into the market, an experiment was first conducted to experiment the treatment effect of this new strategy.

According to the Bureau of Transportation Statistics (10), 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 (11). Nevertheless, a number of cities and some employees have realized that "free parking" is a key contributor to many negative environmental, social, economic and aesthetic externalities, and thus shown increasing interest in more rigorous parking management and pricing (12). Several studies have shown that charging for parking will lead some travelers to move to other commute options (1, 6, 15). UC Berkeley Parking and Transportation office currently price campus parking at $95-131 per month for most faulty and staff members. However, it is still heavily utilized, with recent field observations finding occupancies of 85-90% or higher at most locations for much of the workday (3). Parking price elasticity tends to be quite low, in the range of -.1 to -.3 (4). Thus, even if price increases substantially, many travelers are likely to continue to drive and park, inducing the demand for constructing new parking lots or replacing surface lots to buildings. In Berkeley, cost of new space is high, with construction cost penciled at $65,000 per space and land costs of $7M per acre (14).

The tensions between the high costs of parking and the continued interest in having it available have posed a dilemma for many parking providers. Therefore, it is worthwhile considering whether other modes of transport might be a better way to go. For employment centers located in medium to high density urban locations such as Berkeley, realistic options for travel do exist. The challenge is that employees are unaware of or confused about the travel options that are available, as incentives to use these options may be missing or inadequate. Riggs and Kuo (9) show that a 'soft sell' approach providing better information on available travel options can nudge some drivers to switch modes. Based on the campus survey data, Proulex et al. concluded that if parking demand must be reduce, both price and incentives to use different travel modes would need to be increased (8). In a later project, Ng conducted focus groups, interviews and a stated preference survey and proposed several incentive schemes (7). With such incentives, Ng's model results indicate that it might be possible to reduce the Berkeley on-campus parking demand by an additional 5%. However, the above inference was conducted based either stated preference or observational data, which can hardly support a valid causality link between incentives and reduction in parking demand. In its 2011 proposal to the USDOT's FHWA for a value pricing project, the University of California, Berkeley proposed to test new parking policies and pricing approaches that would reduce the disincentive to be an occasional user of parking rather than a regular monthly parker. The FlexPass study is a part of this program, which have been conducted as a randomized controlled trail with 392 participants during the Spring 2015 semester, February 1st, 2015 to April 30th, 2015.

This paper presented an causal analysis of the treatment effect of the FlexPass. The paper began with a brief introduction of the experimental design, followed by baseline description of enrolled participants' social economic data. Participants longitudinal parking behavior was the displayed. The missing report and dropout problems were also addressed. Missing reports were predicted from follow-up email surveys through a Mixed Latent Factor model. Dropout biases were captured by a sample selection model. The effect size of FlexPass was estimated and insights into the incentive system were developed.

## Experimental Design

This study targets 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. The current price for **F** permit is $95 per month while $131 per month for **C** permit. Participants are only allowed to take part in this study if they have already purchased a **C** or **F** permit for the entire 2015 Spring semester. Enrolled participants will be assigned into two groups, treatment and control group, through a randomized controlled trial. The treatment-group participants are required to exchange the original permit hang-tags to new ones for the study, while those in the control group keeps the original hang-tags.

Both study groups are required to report their daily parking choices via the FlexPass app over the entire study period, which is available in both iPhone and Android platforms. The default choice for every day is "Parked on Campus". This can changed to not park on campus for the day or the next day on the app's main interface or for several days in the future on the app's calendar. If participants indicate that they will not park, they will also be asked to report what alternate mode would be taking or whether they would be coming to campus. Participants are able change their parking decisions for a certain day till 12 noon on that day. Those decisions will be synchronized to our server in real time and will be sent to parking enforcement officers. Participants may receive citations if they park on campus after declaring that they will not.

Participants in the treatment group are eligible for rebates which are based on their permit types and the number of working days (Mon. to Fri.) they park on campus in a given month. Rebate amounts are calculated as equation 1 below.

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

where $D$ is the number of working days a certain participant parks on campus in a certain month and $T$ is the total rebates for the month. The maximum monthly rebate is \$$\Theta$ ($\Theta$=95 for **F** permit holders while 131 for **C** permit holders). For each day parking on campus, a participant will be changed a \$$\delta$ credit ($\delta$ =6 for **F** permit holder while 8 for **C** permit) until all credit has been used up. For example, an **F** permit holder who parks 12 workdays on campus (approximately 3 work days a week) will receive a rebate of $23.[1]

[1] Detail description of the rebate calculation and a table of all possible rebate values can be found in the homepage of our study website https://gogreen.berkeley.edu/flexpass/.

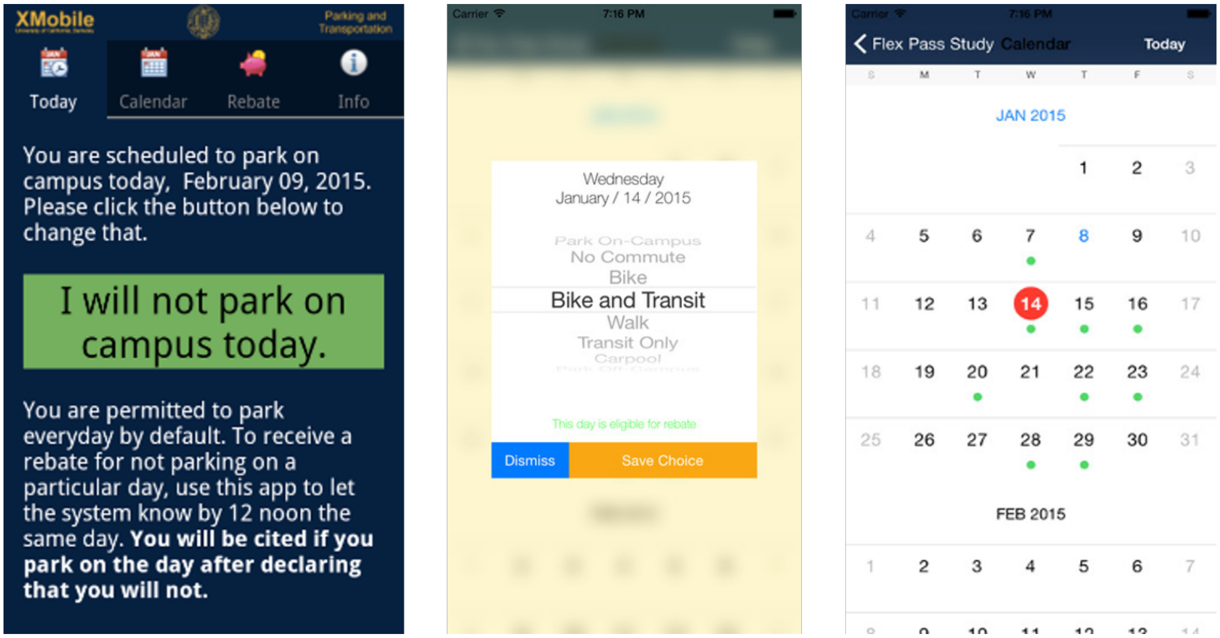



**FIGURE 1** : FlexPass smartphone app interface. From left to right, (a) Main Screen, (b)Mode Reporting, (c) Calendar

### Sample Characteristics

Among the 4272 C&F permit holders at UC Berkeley whom we have reached through emails and postcards, 392 participants finished the sign-up process. They were equally divided into the treatment group and the control group. The demographic and social-economical information is illustrated in table 1. UC Berkeley staff made up the bulk of the sample. Female respondents account for 71 percent of staff and 57 percent of faculties. Respondents tended to be at the middle stages of their life cycle. 30 percent of the enrolled participants have at least one bike while 35 percent have Clipper card, a reloadable contactless card used for electronic transit fare payment in the San Francisco Bay Area. These provide them potential alternative commute modes when plan to forgo parking on campus. 77 percent of the participants enrolled in the study felt interested in the potential rebates they could collect. Rest 33 percent would like to support our research but were not interested in rebates, where 71 people also wrote down the reason for not interesting. Typical reasons includes "must park each work day", "I need to get to my children from time to time" and "No alternatives for me other than driving my car". 54.5 percent of participants also showed interests in potential of knowing parking availability via smartphone app. Respondents are asked about their weekday commute modes in the week previous to the entry survey. 76 percent of the enrolled participants came to campus for all five weekdays. 79 percent of enrolled parking permit holders drove alone and parked on campus for more than 4 weekdays. If they were going to persist this behavior during the study, which is averagely parking on campus for 17 days per month, no rebate could be collected according to the rule of rebate calculation.

**TABLE 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** | | | |
| 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 |
| EIGHT_TEEN_TO_TWENTY_FOUR | 2.5 | 1.6 | 2.0 |
| **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 Interesting** | | | |
| FALSE | 21.4 | 23.0 | 22.2 |
| TRUE | 78.6 | 77.0 | 77.8 |
| **Number of Days Commute to Campus** | | | |
| 5 | 73.7 | 77.6 | 75.6 |
| 4 | 13.4 | 12.2 | 12.8 |
| 3 | 8.6 | 5.6 | 7.1 |
| 2 | 2.7 | 4.1 | 3.4 |
| 1 | 1.1 | 0.5 | 0.8 |
| 0 | 0.5 | 0.0 | 0.3 |
| **Number of Days Drive 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 Participates** | | | |
| | 196 | 196 | 392 |

## CAUSAL ANALYSIS OF THE FLEXPASS STUDY

To infer the treatment effect of the FlexPass, we proposed a box model as shown in figure 2(a). 392 samples were drawn from the box of 4272 C&F permit holders and assigned into treatment group and control group randomly. Given the group assignment $T$, and participants indexed by $i$, $Y_i^T$,$Y_i^C$ denotes the potential outcomes given FlexPass treatment, $T_i = 1$, and non-treatment, $T_i = 0$, respectively. For each participant, 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 participant $i$'s parking choice on day $j$. $Y_{ij}$ equals 1 if he or she did not park on campus on day $j$ and 0 otherwise. Participants' social economic characteristics, denoted as $X_i$ on the ticket, were measured in the entry survey. As only average treatment effect is concerned, the casual analysis will conducted based on the number of days participants not parking on campus during the entire study period, denoted as $y_i$ for participant $i$, $y_i = \sum_j Y_{ij}$. Similarly, let $y_i^T = \sum_j Y_{ij}^T$ and $y_i^C = \sum_j Y_{ij}^C$, the average treatment effect is $E({y^T}_i - {y^C}_i)$. The naive estimator of the causal effect, $E(y|T = 1) - E(y|T = 0)$, should be an unbiased since a randomized controlled trail was conducted. However, problem arisen during the study as not all $Y_{ij}$s are observed, which causes biases in causal analysis.

In this section, missing data and dropout problems will be addressed. The missing data will be imputed by a Mixed Latent Factor Model (MLFM) while dropout bias will be compensated through selection model. The result of casual analysis will then be discussed.

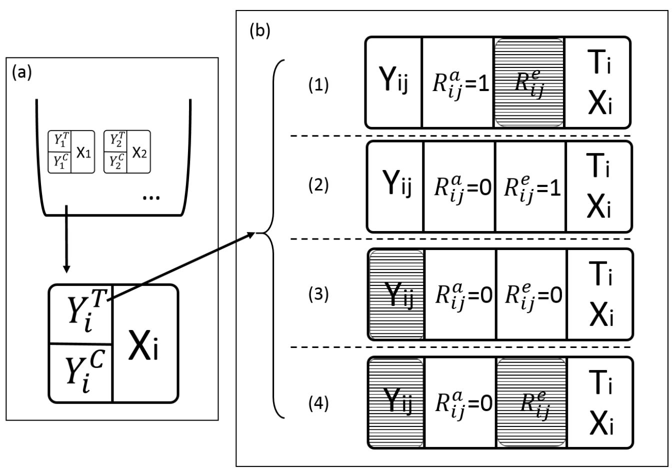
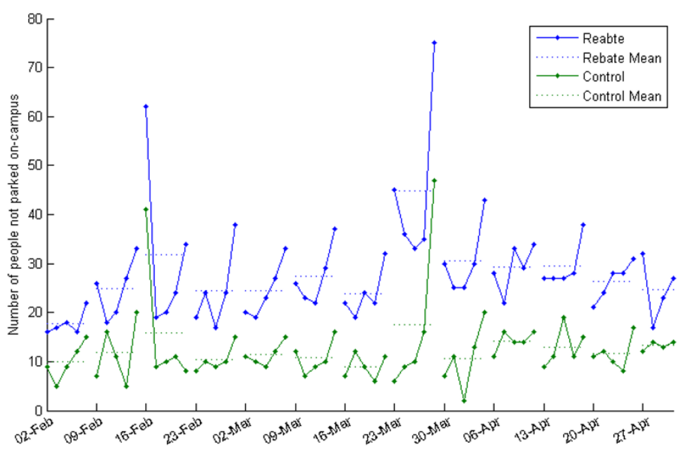


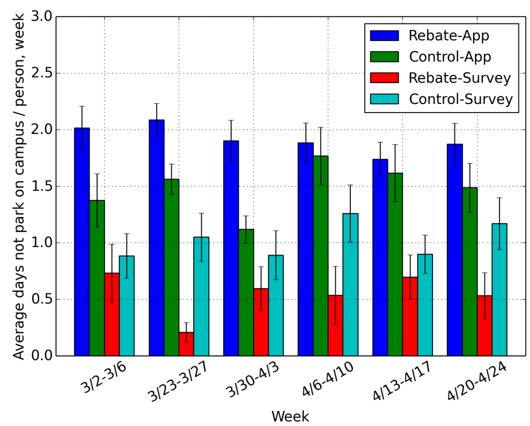

**FIGURE 2** : Box model for causal analysis

### Dropouts, Missing Report Mechanism and Data Descriptions

The app-reported longitudinal data of reduction in daily parking demand is shown in figure 3a. The blue line which represents the treatment group is always above the green line which represents the control group. This may be a indicator for significant treatment effect at the first sight. However, this comparison relies on a strong assumption that when people did not report any thing through the app on certain days, they are considered as "Park On Campus". In fact, from focus group interviews during the study showed that sometimes participants forgot to use the app when did not use campus parking. Especially for participants in control group, there is no incentives for them to report daily commute modes. During the entire study period, there were 74 participants in the control group who reported nothing through our smartphone app. In the treatment group, the number reduced to 38. Even with participants who have reported some parking activities, they may still under report the number of not-park-on-campus days, which led to an overestimation of the treatment effect. Therefore, instead of respond $Y_{ij}$, we additionally define, for each occasion j, an indicate $R^a_{ij}$, which equals 1 if participant $i$ reported day $j$'s parking behavior through smartphone app and 0 if participant $i$ didn't 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. $Y^m_i$ is referred to missing reports. To further understand the missing report process, we sent commute mode surveys in the 6 weeks during the study to those who had not used their smartphone app for a week prior to the survey. The survey inquired participants about their daily commute choices in the past week. The average respond rate for the email survey is 62.2%. Hence for each occasion j, another indicator is defined as $R^e_{ij}$, which equals 1 if participant $i$ 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 responds

**FIGURE 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) [Rubin 1976, Little and Rubin 1987]. The three mechanisms differ from each other based on the dependencies between missingness and observed and unobserved data. MCAR refers to the missingness is independent of both observed and unobserved data; MAR refers to missingness is independent of unobserved data; MNAR refers to missingness is 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 participants 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 out comes from follow-up emails with app reports showing in figure 3b. It can be observed that the email responses of non-campus parking days is generally lower than the app reports. In those 6 weeks when surveys were sent, the app reports resulted in averagely 1.92 non-campus parking days per week among the rebate groups, while this number is 0.57 for email responds. 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 and will be modeled through a Mixed Latent Factor Model (MLFM) in the next section.

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(b), where the shaded region means not observable. In situation (1), participant i report day j's parking choice through the app, where $Y_{ij}$ is observed and no email will be sent. In situation(2) , participant i didn't use the app on day j and an email will be sent to i. The participant answered the email and thus $Y_{ij}$ is observed. In situation(3), $Y_{ij}$ is not observed as participant i didn't answer the email. Situation(4) may happen when participant i droped out from the study that neither did she/he use the app nor did she/he receive any email. Noticeably, all $Y_i^o$ is observed in this study by definition and part of $Y_i^m$ is measured in situation (2). If $Y_i$ only contains $Y_{ij}$ of situation (3) and (4), participants i is regarded as 'Dropout Participants'. Otherwise, complete data $Y_i$ will be recovered from $Y_{ij}$ observed in situation (1) and (2).

## Recover Missing Reports

The Latent Factor Model(LFM), also called Matrix Factorization Model, is widely applied in recommendation systems in the search engine, movie and music industry for matching users and potential items that they would be interested in (2, 5). It has been shown that the LFM's are superior over attribute based models, which is often used in transportation studies, in terms of prediction accuracy (5). The idea behind LFM is that preference of a user and attitudes of an item are determined by a small number of factors. The factors of a user or an item can be represented as vectors $\mathbf{U_i}$ or $\mathbf{V_j}$, respectively. These latent factors are capable utilizing observed user-item interactions for predicting unobserved interactions, $Y_{ij}$.

$$Y_{ij} = \mathbf{U_i}'\mathbf{V_j} + \varepsilon_{ij} \tag{1}$$

applying the concept to the FlexPass study, we regard the study participants and the working days during the study period as 'users' and 'items', while parking choice matrix $Y$ as rating matrix. Denote the number of participants as M and number of working days as N. $Y_{i,j}$ stores participant i's parking choice on day j. To illustrate the idea of LFM, we first assume for all i and j, $Y_{ij}$ is generated by from the same process described in equation 1 with $\mathbf{U}$ and $\mathbf{V}$ unknown. $\mathbf{U}$ and $\mathbf{V}$ is a $M \times L$ and $N \times L$ matrix respectively, where $i^{th}$ row of $\mathbf{U}$ is referred as participant i's latent factor while $j^{th}$ row of $\mathbf{V}$ is referred as day j's latent factor. When $\varepsilon_{ij}$ is independent and identically Gaussian distributed (i.i.d. Gaussian), the estimated parking respond matrix $\hat{Y}$ can be expressed by $\mathbf{U}'\mathbf{V}$. Let $\|.\|_F$ denotes Frobenius norm, to maximize the prediction accuracy of rating matrix equals to solve:

$$\min_{rank(\widehat{\mathbf{Y}})\leqslant \mathrm{L}} \left\|\mathbf{Y}-\widehat{\mathbf{Y}}\right\|_F$$

whose solution is essentially a singular value decomposition(SVD) of $\mathbf{Y}$. Optimal $\hat{\mathbf{Y}}^*$ and corresponding prediction error can be expressed by:

$$\hat{\mathbf{Y}}^* = \sum_{i=1}^{L} \sigma_i u_i {v_i}'; \quad \left\|\mathbf{Y} - \hat{\mathbf{Y}}^*\right\|_F = \sum_{i=L+1}^{rank(\mathbf{Y})} {\sigma_i}^2$$

where $\sigma_i$ is known as $i^{th}$ singular values of $\mathbf{Y}$, $u_i$ and $v_i$ is called the $i^{th}$ left-singular vector and right-singular vector, respectively. These singular vectors are often regarded as latent semantic factors in information retrieval. In the FlexPass study, the full dataset should contain $292 \times 64 = 18688$ responds, while in reality we collected 8093 app responds and 2609 email responds, which account for 57% of the full dataset size. Since the sum-square distance can be computed only for the observed entires of the target sparse matrix $\mathbf{Y}$, as shown by (13), this seemingly minor modification results in a difficult non-convex optimization problem which cannot be solved using standard SVD. LMF is closely related to SVD but models directly the observed ratings while avoid overfitting through a regularized model. Noticeably, the key underlying probabilistic foundation for LFM is that the error term in equation 1 is i.i.d. Gaussian which implies the missing data mechanism is considered as MCAR.

To model MNAR mechanism, we proposed a Mixed Latent Factor Model(MLFM), where $Y_{ij}$ generated from two different processes depending on whether $Y_{ij}$ is observed through app reporting, ${R^a}_{ij} = 1$, or otherwise ${R^a}_{ij} = 0$.

$$Y_{ij} = (1 - {R^a}_{ij}){\alpha^m}_i + {R^a}_{ij}{\alpha^o}_i + \beta_j + \mathbf{U_i}'\mathbf{V_j} + \varepsilon_{ij}; \quad \varepsilon_{ij} \sim \mathcal{N}(\varepsilon|0, \sigma^2) \tag{2}$$

where $\beta_j$ is the weekday specified constant for day j; $\alpha_i^o$ is the participant specified constant for participant i when app report observed, ${R^a}_{ij} = 1$; and $\alpha_i^m$ is the participant specified constant when app report missing, ${R^a}_{ij} = 0$. $\mathcal{N}(x|\mu, \sigma^2)$ is the probability density function (pdf) of the Gaussian distribution with mean $\mu$ and variance $\sigma^2$. $R_{ij}^a$ is the app report indicator defined in section 3.1. The MNAR mechanism is modeled by two participant specific constant parameters. $Y_{ij}$ depends on $\alpha_i^o$ if app report exists while depends on $\alpha_i^m$ if otherwise. More complicated Mixed-LMF can be created where $\mathbf{U_i}$ is also different for app reports and missing reports. However, this will add $M \times L$ more parameters to the model which largely increases the computation complexity. Also, absorbing heterogeneity of app report responds $Y_i^o$ and missing reports $Y_i^m$ by two M dimension vectors leads to more clear interpretations. To prevent over-fitting, we also place zero-mean spherical Gaussian priors on latent factors:

$$p(\alpha^o|{\sigma_{\alpha^o}}^2) = \prod_{i=1}^{M} \mathcal{N}({\alpha^o}_i|0, {\sigma_{\alpha^o}}^2\mathbf{I}), \quad p(\alpha^m|{\sigma_{\alpha^m}}^2) = \prod_{i=1}^{M} \mathcal{N}({\alpha^m}_i|0, {\sigma_{\alpha^m}}^2\mathbf{I}), \quad p(\beta|{\sigma_\beta}^2) = \prod_{j=1}^{N} \mathcal{N}(\beta_j|0, {\sigma_\beta}^2\mathbf{I})$$

$$p(\mathbf{U}|{\sigma_U}^2) = \prod_{i=1}^{M} \mathcal{N}(\mathbf{U_i}|0, {\sigma_U}^2\mathbf{I}), \quad p(V|{\sigma_V}^2) = \prod_{j=1}^{N} \mathcal{N}(V_j|0, {\sigma_V}^2\mathbf{I})$$

The corresponding graphic model for Mixed Latent Factor model is shown in figure 4. The log of posterior distribution over the latent factors is given by

$$\begin{aligned}\ln p(\alpha^{\mathbf{o}},\alpha^{\mathbf{m}},\beta,\mathbf{U},\mathbf{V}|\mathbf{Y},\mathbf{R},{\sigma_{\alpha^o}}^2,{\sigma_{\alpha^m}}^2,{\sigma_\beta}^2,{\sigma_U}^2,{\sigma_V}^2) \propto \\ \ln p(\mathbf{Y}|\mathbf{R},\alpha^{\mathbf{o}},\alpha^{\mathbf{m}},\beta,\mathbf{U},\mathbf{V}) + \ln\prod_{i,j}\mathcal{N}({\alpha^o}_i|0,{\sigma_{\alpha^o}}^2\mathbf{I})^{{R^a}_{ij}} + \ln\prod_{i,j}\mathcal{N}({\alpha^m}_i|0,{\sigma_{\alpha^m}}^2\mathbf{I})^{(1-{R^a}_{ij})} \\ + \ln p(\beta|{\sigma_\beta}^2) + \ln p(\mathbf{U}|{\sigma_U}^2) + \ln p(\mathbf{V}|{\sigma_V}^2)\end{aligned}$$

Maximizing the log-posterior over latent factors with hyper-parameters, i.e. prior variances, kept fixed is equivalent to minimizing the sum-of-squared-errors objective function with quadratic regularization terms. Furthermore, to control the number of hyper-parameters,we set $\sigma_{\alpha^o}$=$\sigma_{\alpha^m}$= $\sigma_\beta$ and $\sigma_U$=$\sigma_V$.

$$\begin{aligned}\min\sum_{i,j} I_{ij}\{[Y_{ij} - (1-{R^a}_{ij}){\alpha^m}_i + {R^a}_{ij}{\alpha^o}_i + \beta_j + \mathbf{U_i}'\mathbf{V}]^2 \\ + \lambda_{\alpha\beta}[{R^a}_{ij}\alpha^{o2}_i + (1-{R^a}_{ij})\alpha^{m2}_i + {\beta_j}^2] + \lambda_{UV}({U_{ij}}^2 + {V_{ij}}^2)\}\end{aligned} \quad (3)$$

where $I_{ij}$ is the indicator function of all observed data that $I_{ij} = R^a_{ij} + R^e_{ij}$ and $\lambda_{\alpha\beta} = \sigma^2/\sigma^2_\beta$, $\lambda_{UV} = \sigma^2/\sigma^2_U$. A local minimum of the objective function given by equation can be found by perform gradient descent in $\alpha^{\mathbf{o}}$,$\alpha^{\mathbf{m}}$, $\beta$, $\mathbf{U}$ and $\mathbf{V}$.

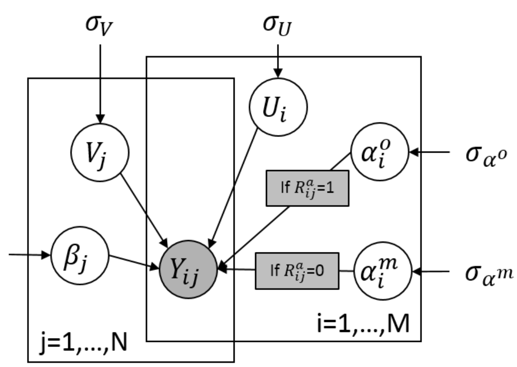



**FIGURE 4** : Graphic Model for Mixed Latent Factor Model

To apply the MLFM to our data, we first removed "dropouts", which results in 306 valid users in our MLFM, $M = 306$. All weekdays during the study are also included, which leads to $N = 64$. Dimension of latent factors L is set to be 10. As we penalize the norms of parameters, the model performance will not be sensitive to L. At the occasion i,j where the respond is missing, we predict that participant i will not park on campus on day j if the $\mathbf{Y}$ estimated from equation 2 is larger than 0.5. A 5-fold cross validation was conducted to choose optimal $\lambda_{UV}$ and $\lambda_{\alpha\beta}$. The original sample is randomly partitioned into 5 equal sized subsamples. Every round, a single subsample is retained as the validation data for testing the model, and the remaining 4 subsamples are used as training data. The cross-validation process is then repeated 5 times and the 5 predicting errors can then be averaged to produce a single estimation called cross validation error. $\lambda_{\alpha\beta} = 0.5$ and

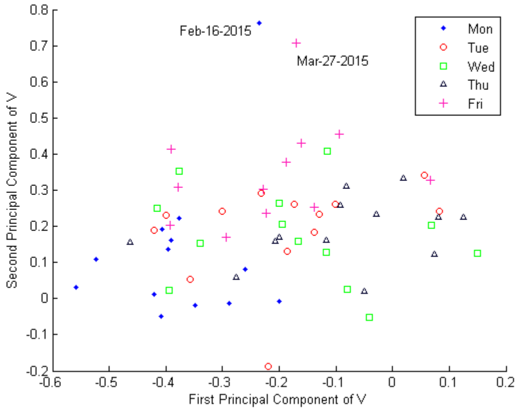
$\lambda_{UV} = 0.05$ results in the best overall cross validation error of 20.88%. For participants in control group, the false positive rate $p(\hat{Y}_{ij} = 1|Y_{ij} = 0, T_i = 0)$ is 19.07% while the false negative rate $p(\hat{Y}_{ij} = 0|Y_{ij} = 1, T_i = 0)$ is 18.09%. For participants in treatment group, the false positive rate $p(\hat{Y}_{ij} = 1|Y_{ij} = 0, T_i = 1)$ is 13.61% while the false negative rate $p(\hat{Y}_{ij} = 0|Y_{ij} = 1, T_i = 1)$ is 25.39%. Although the false positive and negative rate is imbalanced for treatment population, it systematically under-predicts the number of non-campus parking days, which will lead to a conservative estimation of treatment effect.

We compare the difference between MLFM and attribute based model by building a random forest model. The random forest model predicts the $Y_{ij}$ using social-economic features collected from the entry survey with each $Y_{ij}$ considered independent. The random forest resulted overall cross-validation error of 23.66%. For participants in treatment group, the false positive rate $p(\hat{Y}_{ij} = 1|Y_{ij} = 0, T_i = 1)$ is 12.78% while the false negative rate $p(\hat{Y}_{ij} = 0|Y_{ij} = 1, T_i = 1)$ is 50.61%. The random forest model has significantly higher false negative rate than the MLFM, which led to a worse over cross-validation error. This is due to the disadvantage of feature based models in capturing heterogeneities in participants' behavior with limited features.

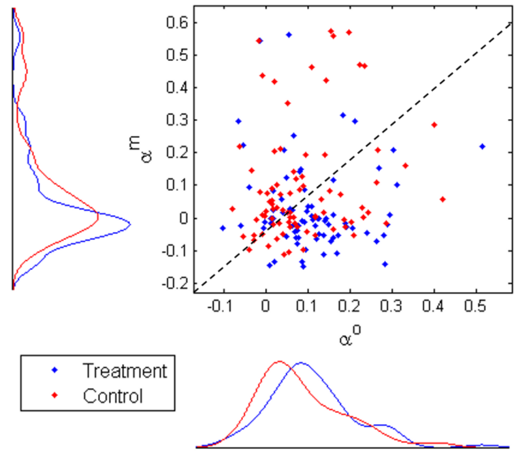
In the estimated MLFM model, there are L latent components in both factor matrix $\mathbf{U}$ and $\mathbf{V}$. Similar to the standard SVD, we rank these components by their information amount, where first we calculate ${\sigma_l}^2 = \sum_{i=1}^{M} {U_{il}}^2 + \sum_{j=1}^{N} {V_{jl}}^2$ and sort $\mathbf{U}$ and $\mathbf{V}$ in the way that $\sigma_l^2 \geqslant \sigma_{l+1}^2$ for all $l = 1, ..., L$. $l^{th}$ column of the new factor matrix $\mathbf{U}$ and $\mathbf{V}$ is denoted as $l^{th}$ principal component of $\mathbf{V}$. Weekday latent factor matrix $\mathbf{V}$ is visualized by its first and second principal component in figure 5a. Different weekdays are drawn with different color and markers. Patterns can be observed such as Fridays are mainly distributed on the upper part while Mondays on the lower left. Features of two holidays are captured in the model as their latent factors depart from the population. In order to show how MNAR mechanism is captured in participant specific constant parameters, a scatter-hist plot for $\alpha_i^o$ and $\alpha_i^m$ is drawn for every valid participant i on figure 5b. with kernel density of $\alpha^o$ and $\alpha^m$ projecting on x and y axis. It can be observed from the scatter plot that for participants in treatment group, 73% of the blue dots are below the 45 degree dash line, meaning that $\alpha_i^o > \alpha_i^m$, which is in line to with the information shown in figure 3b. From the kernel density plot for $\alpha^o$ we can observe that the distribution of $\alpha^o$ for treatment group is shifted to the right of control group, meaning the app reports revealed that treatment group forwent parking on campus more often. The kernel density plot for missing report participant-specified constant $\alpha^m$ shows the opposite result. $\alpha_i^m$ for treatment group are concentrating at rather low values, meaning that the missing report rate of treatment participants is rather small. $\alpha^m$ distribution of control group shows similar pattern as its $\alpha^o$ distribution, capturing control participants often forgot to report when they did not park.

## Compensate Differential Dropout Bias

For valid participants, $y_i$ can be calculated from the recovered parking respond matrix $\hat{\mathbf{Y}}$, such that $y_i = \sum_{j=1}^{N} \widehat{Y}_{ij}$. For dropout participants, i.e. participants in the treatment group did not pick up the FlexPass hang tag and people in control group did not report any parking




(a) First and second principal component of **V**




(b) Scatter-hist plot for participant specific constant parameters $\alpha^o$ and $\alpha^m$

**FIGURE 5** : Visualization of latent factors

choice during the study, their $y_i$'s are unobservable. We denote a dropout indicator $R_i^d$, where $R_i^d = 0$ if participant 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 confounder. Existence of in randomized controlled trails, e.g. FlexPass Study, experiments of new drug impact, are not rare. 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 (**?** ). Additional information are 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 is explicit known in our study, sample selection model was employed.

We first consider a homogeneous treatment effect $\delta$ which does not vary over individual. The sample selection model with differential consists the following structural process:

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

where $R_i^{d*}$ is the realization of the latent value of the selection "tendency" for the participant i, and $y_i^*$ is the latent outcome of total non-campus parking days during the study. ${X_i}^O$ are explanatory variables including some background characteristics of enrolled participants. ${Z_i}^S$ are explanatory variables for the selection equation. Identification requires ${X_i}^O$ 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 and is due to different reason, a differential dropout process is modeled. ${\beta_T}^S$ and ${\beta_C}^S$ represents parameters describes distinct dropout processes for treatment and control group respectively. We observe:

$$R^d{}_i = \begin{cases} 0 & if\ R^{d*}{}_i < 0 \\ 1 & otherwise \end{cases}$$

$$y_i = \begin{cases} unknown & if\ R^d{}_i = 0 \\ y_i{}^* & otherwise \end{cases}$$

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

$$E[y|T = T_i, R^d = 1, X^O = X^O{}_i] = \beta^{O\prime} X_i{}^O + \delta T_i + E[\varepsilon_i{}^O | \varepsilon_i{}^S \geqslant -[T_i \beta_T{}^S + (1 - T_i)\beta_C{}^S]' Z_i{}^S] \quad (4)$$

The third term in equation 4 illustrates why the naive estimator using observed data gives in general 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 mean independent, e.g. the dropout process is completely random. Parameters can be estimated effectively through maximal likelihood method by assuming the error terms follow a bivariate normal distribution (**?** )toomet2008sample):

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

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

The probit results for selection process in TABLE 2 offer clear insights into the value of different social economic features in explaining the probability of dropout in treatment and control groups. Participants who stay valid in treatment group are essentially who went to the P&T office in person and changed to the new hang-tag, which can be viewed as a extra time cost. The table suggests that owning a Clipper card decrease the odds of dropping off in treatment group; being interested in rebates increased the probability of stay valid even more. Indeed, the selection process implied that there may exists a "positive selection" that people with potential alternative commute modes and with willingness to collect the rebate tend to remain active in the treatment group. For control group, participants who never used the app and replied the email survey were considered as dropped out. We found that participants who prefer to receive information through channels other than smartphone app tend to drop out. Being senior, 55-year-old or elder, increased the odds of not reporting parking behavior. Furthermore, participants who had commuted to campus less often before the study began were going to stay valid in control group. We interpret this as those in this category forwent parking on campus more often and thus were more likely to remember to use the app.

The regression result for measurement equation in sample selection model is shown in TABLE 2. Two ordinary least squares (OLS) regressions were also conducted directly based

**TABLE 2** : Selection equation

| | *Dependent variable:* | |
|---|---|---|
| | TreatmentValid | ControlValid |
| | (1) | (2) |
| Age Group.SENIOR | 0.116 | $-0.666^{**}$ |
| | (0.314) | (0.297) |
| Gender.MALE | 0.307 | 0.027 |
| | (0.265) | (0.222) |
| Has Bike.TRUE | 0.420 | 0.241 |
| | (0.270) | (0.236) |
| Has Clipper Card.TRUE | $0.541^{**}$ | 0.030 |
| | (0.257) | (0.218) |
| Berkeley Staff.TRUE | $0.665^{**}$ | 0.251 |
| | (0.271) | (0.270) |
| Days Not Commute | $0.159^{*}$ | $0.204^{**}$ |
| | (0.089) | (0.092) |
| Rank Mobile App | 0.084 | $-0.191^{*}$ |
| | (0.132) | (0.114) |
| Rebate Interesting.TURUE | $0.793^{***}$ | $-0.340$ |
| | (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 |

on 306 observed parking responds as baseline. All the four models gave similar estimations for the effect of being UC Berkeley staff members. They significantly parked about 4 days more than faculties. It can be explained by their more restricted working schedules. The regression also showed that participants owing bikes parked on campus less often. First considering model (1) and (3), where the homogeneous treatment effect was estimated. The selection model suggested a barely significant average treatment effect of 2.295 days reduction of on campus parking per participant during 3 months. The correction between selection and observation process $\rho$ 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, biased. We further consider the existence of heterogeneous treatment effect, where FlexPass' treatment effect varied among different types of individual. This is captured by an interaction term in model (2) and (4). In the sample selection model with interaction term, model (4), there is indeed no significant treatment effect of FlexPass for people who had reported not interested in the rebate. According to the entry survey, before the study rebate-not-interested participants parked on campus for 4.6$\pm$1.1 days, while rebate-interested participants parked on campus 4.1$\pm$ 1.3 days. Rebate-not-interested participants generally have a hard demand for driving and parking on campus, with small price elasticities. Before the experiment. The size of treatment effect on rebate-interested participants was 3.372 days with standard error 1.436 (The covariance between the coefficients of interaction term and treatment $T$ was -8.024). This results in a p-value of 0.017, which is considered as significant effect.

As mentioned before, MFLM underestimated number of non-campus parking days for treatment group. Sample selection model, compared OLS, produced conservative estimator of the treatment effect. Although our estimation of treatment effect may be still biased, it is in the safe direction. Therefore we concluded that FlexPass did changed participants' parking behavior. On the population level, the treatment effect of FlexPass was 2.23 days per participants, which is a 0.18 day reduction per week. This 4.2% demand reduction is close to the 5% Ng inferred from the focus group and stated preference survey (7), but slightly smaller. There is no significant treatment effect for people who were regular drivers. For participants reported interested in the incentives, which is 77.8 percent of the population, FlexPass induced a 3.372 days on campus parking demand reduction per participant, which is a 0.26 day reduction per week, a 6.0% demand reduction. Therefore, if we are going to increase the parking price of the regular monthly permit and provide incentives at the same time, regular driver with low price elasticities will stay on the monthly permit who pay the extra price, while drivers who are willing to adopt other modes can benefit from the rebate.

## CONCLUSION

Due to the low elasticities of campus parking demand and absence of incentive programs, the Parking and Transportation office of University of California, Berkeley has proposed the FlexPass for encouraging campus employees to park less on working days. Before the FlexPass is launched on the market, we conducted the FlexPass study to experiment the treatment effect of the new pricing strategy on a population of 392 UC employees. The 3-month study lasted from February 1st to April 30th, 2015 with 8093 responds from the smartphone app and 2609 responds from email survey were collected.

We presented an causal analysis of the treatment effect of the FlexPass using the

**TABLE 3** : Casual Inference Results

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | noPark | | | |
| | *OLS* | | *selection* | |
| | (1) | (2) | (3) | (4) |
| Rebate | 2.841** | −2.836 | 2.295* | −1.978 |
| | (1.257) | (2.792) | (1.279) | (2.814) |
| Berkeley_Staff | −4.010*** | −3.907** | −4.430*** | −4.300*** |
| | (1.532) | (1.522) | (1.551) | (1.535) |
| Age_Group.Senior | 0.969 | 1.308 | 1.650 | 1.812 |
| | (1.942) | (1.934) | (1.967) | (1.949) |
| Has_Bike | 2.750** | 2.960** | 2.253 | 2.484* |
| | (1.370) | (1.363) | (1.393) | (1.383) |
| Rebate_Interesting.new | 3.279** | 0.149 | 2.758* | 0.414 |
| | (1.594) | (2.098) | (1.611) | (2.107) |
| Rebate:Rebate_Interesting.new | | 7.089** | | 5.435** |
| | | (3.118) | | (3.193) |
| Constant | 8.481*** | 10.653*** | 7.182*** | 9.501*** |
| | (2.055) | (2.254) | (2.241) | (2.386) |
| Observations | 306 | 306 | 400 | 400 |
| $R^2$ | 0.085 | 0.101 | | |
| Adjusted $R^2$ | 0.070 | 0.083 | | |
| Log Likelihood | | | -1,354.243 | -1,352.815 |
| rho | | | 0.405*** | 0.356** |
| | | | (0.122) | (0.141) |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

longitudinal parking behavior data using the box model. There were two biases that we have estimated using the Mixed Latent Factor Model (MLFM) and the selection model. The missingness in the app report is Missing Not At Random (MNAR), which is shown by results from the email surveys. We proposed the MLFM for modeling the missingness and for recovering the missing data. The MLFM resulted 20.88% cross-validation error rate, which outperforms the best feature-based model that we have experimented. Dropout biases were addressed by a sample selection model. We present both OLS and selection model and the selection model has a conservative result. Among the entire group of participants, the treatment effect of FlexPass is 2.23 days over the study period, which is a 4.2% demand reduction. However, this treatment effect only showed significance among participants with rebate interests.

In the FlexPass study, we totally issued $4256 rebate to participants in the treatment group. On average, for the 158 valid participants in the treatment group, each participant received $26.94 for forgoing parking on campus over the entire study period. The highest rebate for an individual was $285 while most of others remained under $20. Therefore, the FlexPass study showed the potential of freeing parking resources from a portion of campus employees via incentives. Those spaces could be reused by other employees or visitors. If the FlexPass becomes sustainable commodity for every employees at UC Berkeley, the rebates for forgoing parking need to covered. A potential solution could be raising the original parking price. Since the campus parking demand is rather inelastic, the increase in the revenue could be sufficient to cover the rebates. Thus, a change in the parking policy could be an efficient way to address the campus parking shortage.

The FlexPass study has experimented the The FlexPass study has experimented the incentives using fixed price schemes. Under the fixed price incentives, the willingness to accept for each individual for forgoing campus parking is not observed. Future study could be designed with flexible rebate schemes such that participants report their daily true willingness to accept for choosing alternative commute methods. In such way, the demand of campus parking can be better understood.

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