Optimizing Two Sided Promotion for IS Enabled Transportation Network: A Conditional Bayesian Learning Model

Completed Research Paper

Jinyang Zheng
University of Washington
Foster School of Business
Box 353226
Seattle, WA 98195-3226
zhengjy@uw.edu

Fei Ren
Peking University
Guanghua School of Management
Wusi Rd, Haidian, Beijing, China
fren@gsm.pku.edu.cn

Yong Tan
University of Washington
Foster School of Business
Box 353226
Seattle, WA 98195-3226
ytan@uw.edu

Xi Chen
Nanjing University
Nanjing University Business School
22 Han Kou Lu, Gulou, Nanjing,
Jiangsu, China
chenx@nju.edu.cn

Abstract

This paper investigates a typical two-sided micro-level business model of IS enabled transportation network. Specifically, we focus on how two-sided sales promotion interacts with users' learning about attribute, and measure the effectiveness of sales promotion for their platform introductions. Our paper applies Bayesian learning model with an extension to account for multiple serial unobserved correlation. We find the measurable evidence of taxi driver's learning about order commitment and payment methods of passenger. We furtherly identify that the attribute value of transportation network is undervalued in prior, which indicates that intensive promotion would not only attract user instantly, but also enhance user learning in long run. We name the effect on adoption rate driven by user learning as indirect effect of sales promotion. By running simulations, we quantify the indirect effect of sales promotion explicitly, and furtherly propose more efficient sales promotion strategy as managerial implication for industry.

Keywords: innovative business model, transportation network companies, two-sided sales promotion, Bayesian learning, structural model

Introduction

Information system never stops its expedition into reshaping traditional business. One recent progress of information system's expedition is "transportation network companies" (we use TNC in short interchangeably), which is defined as "a service that does not own vehicles or employ drivers, and relies on software to connect passengers to rides". Early runners of transportation network App include well-funded firms, such as Uber, Lyft, Hailo, OlaCabs, and Didi Dache. Typical TNCs provide a two-sided market with two versions of App: one for taxi drivers and one for passengers. Both versions can be easily downloaded from major App platforms including App Store, Google play and Apps for Window Phone. With App installed, passengers can input information specifically about their trip into the system to personalize their

orders, such as pick-up location, destination and other requirements. Drivers can also personalize by picking an order which fits their latent priority scheme, such as optimization of route or profitability.

Information system creates value for different parties of stakeholders through the following formats. For taxi drivers, such app provides attribute value. The attribute value here refers to the aggregates of characteristics value of the TNC app. Other researchers might use quality interchangeably (Erdem and Keane, 1996; Chen et al 2008). For app usage, attribute value includes but is not limited to functions like extended passenger pool and part of prior information about an order. Compared with traditional taxi drivers, TNC drivers extends the passenger pool from hotline-reserved and eyesight-reached road-side customers to a pool in which customers can be miles away. Furthermore, taxi drivers can select customers based on prior information about pickup location, destination, tips and other requirements to generally match their preference of driving areas and routines. Even though that the prior information might be partial and biased, it might still significantly reduce operations cost in general.

For taxi riders, TNC app provides value by simplicity and flexibility in transaction process. The most prominent functions are cancelling and online-pay. Customers might have different preference across different transportation conditional on weather and timing. In the traditional reservation-based transportation model, once a reservation is made, it incurs cost if passengers change their minds. With cancelling function, passengers can easily adjust their preference based on updated information about ordered TNC taxis through apps and instant information about outside goods from other channels. Such a process further maximizes passengers' utility. Online-pay, on the other hand, enables customers to handle their financial transactions automatically. Typical TNC taxis charge passengers once a transaction is finished, and report the routine, time and amounts through email at the same time. Passengers can dispute once they receive email. It simplifies business process during taxi riding period, and saves time for both drivers and passengers. Furthermore, such function allows passengers to be reached by sales promotion easily and effectively.

For app providers, TNC app provides a channel in which two-sided promotion can be conducted. Promotion for innovative online-to-offline experience goods is a common practice in industry during introduction period. Majority of startup firms who run frequently purchased experience goods or services believe that it is worthy promoting intensively to enhance users' experiences, which can finally convert to "habit". Such conversion only has one direction for the product whose attribute value is above traditional ones. Once users are converted, they would hardly switch back in equilibrium of promotion-free setting. In other words, such sales promotion generates not only direct effect of increased demand, but also indirect effect in long term, in which customers fully perceive value of new products, and turn to be loyal. The earlier such promotion conducted, the earlier customers are converted, and the faster a firm can generate profit in equilibrium setting with large market share. Such question is consistent with consumer learning literatures.

In addition, TNC app allows platform provider to run two-sided sales promotions. As two sided market provides a platform which attracts both of supplier and demand, a two-sided sells promotion refers to sales promotion applies to both sides of market. Take our taxi market as an example, during the period of sales promotion, both of taxi driver and passenger would enjoy cash back offer conditional on a successful transaction with online payment. It provides a more flexible marketing mix tool for platform provider. However, it brings much more challenge to measure the effectiveness of sales promotion since the decision of one side might depends on the sales promotion for the other side.

To quantify values of attribute and function for passengers and drivers, and to identify effectiveness of both direct and indirect effects of sales promotion in two-sided market are very challenging. Both of indirect effect of sales promotion and the potentially biased perceived value of new functions and attribute during introduction period brings necessity to explicitly model the difference between true value and perceived value of attribute across different time periods. Traditional Bayesian learning model is limited in accounting for such difference for one attribute with multiple forms of information updating. However, in our setting, we need to account for multiple attributes learning since attributes for two sides are obviously different, even though finally they are both learnt by one side.

In this paper, we answer one set of questions: (1) how does two-sided sales promotion make impact on drivers' propensity to use? How does two-sided sales promotion interact with drivers' learning dynamically? And how should we design a better promotion to fasten drivers' learning while being

cost-savvy. We build a structural model about drivers' decisions of accepting orders from App or not. By identifying conditional dependence among decisions of different sides of users, we apply structural model literature about two-sided decisions (Arcidiacono, 2005) and propose a conditional Bayesian learning model, in which we can handle multiple learnings with two-stage estimation. Our result quantifies drivers' learning of app attribute value, passengers' attribute value by using online pay, and passengers' attribute value by committing to an order. We also find that reward from passengers, subsidies from app providers, cash back bonus for passengers and cash back bonus for drivers have impact on drivers' decisions through not only direct impact on latent utility of taxi drivers, but also drivers' belief in passengers' decisions of using pay online and commitment to orders. Our counterfactual analysis identifies the direct effect and indirect effect of sales promotion, and provides some managerial implications for similar App providers about how to fasten consumer learning while being cost-savvy.

Literature Review

Our research is related to the literature of dynamic between empirical consumer learning and sales promotion. A large quantity of industry anecdotes identify sales promotion in introduction period as a strategy to enhance users' experiences and to foster consumer learning. However, in most setting of experience goods with adequate variation of prices, sale promotion is limited in direct effect, which is equivalent to temporary price cut. Consequently, very little academic research pays attention to tease out indirect effect of sales promotion from price. There are exceptions as Erdem and Sun (2002). In their research, they investigate and find evidence of the spillover effects of sales promotion and advertising in umbrella branding of multiple products. In Chen et al (2008), they investigate another extreme case of sales promotion as permanent price cut for cigarettes. In our empirical setting, we identify the indirect effect of sales promotion through consumer learning. In addition, we investigate sales promotion in the format of two-sided promotion. Such promotion mix is widely utilized by e-business and generates richness of innovative marketing mix. Our counter-factual analysis brings insights of how to optimize such promotion.

In methodology, our research applies Bayesian learning model. Erdem and Keane (1996) firstly identifies customer learning about quality levels through experience and unobserved signals as advertising by applying Bayesian updating process. Due to its applicability with consumers' choices under uncertainty, learning model is widely extended to account for more information, such as learning from observed signal (Erdem et al 2008); learning from online reviews with different credibility (Zhao et al 2013), and with different weights, own preference for multiple attributes and variance of preference (Wu et al, forthcoming). Also learning model has been modified to fit in more complex context. Researchers apply the model to pharmaceutical treatment (Crawford and Shum, 2005; Chan and Hamilton, 2006), addictive product as cigarettes (Chen et al, 2008). In information system research, learning model has been applied to content generation and consumption on mobile internet (Ghose and Han, 2011), ideation on crowdsourcing (Huang et al 2014), and online reviews (Ho, forthcoming). In our paper, we extend Bayesian learning model by accounting for learning about multiple conditional attributes. We make decision makers not only learn about product attributes for him/herself, but also learn the attribute levels of the other side to form expected utility.

Our research is also the first paper investigating on-demand TNC Apps from information system perspective. Even though TNC Apps attract lots of attention from industry and media, there is limited research conducted on this topic. Some preliminary research focuses on general impact of this newly introduced product on traditional taxis or public transit system. Rayle et al (2014) find that ride-sourcing complements traditional taxis and public transit by introducing younger customers, while competing with traditional taxis and public transit in the pie of traditional passengers. They also find that ride-sourcing wins traditional taxis in terms of shorter wait time, and wins public transit with respect to overall deliver time. By constructing a model of cost of transaction and regulation, Li et al.(2014) show that total cost and stakeholders cost decrease by utilizing taxi Apps, and suggest using taxi Apps to replace current taxi-calling system with centralized management from government. Other than traditionally assessed efficiency benefits, Li and Zhao (2015) find that TNC Apps can reduce the rent-seeking behavior of taxi dispatchers while humanizing the relationship between drivers and passengers by conducting interviews with drivers, passengers, regulators, association leaders, app providers and developers. There is also some information system research around this topic. By using a study case of a taxi app, Tan et al.(2015) find

that taxi app can use gamification to enable digital disruption through situational and artifactual affordances approach. However, so far our paper is the first to explain TNC app business model from micro level. Our paper complements the research above by modelling transactional level behaviors of TNC app users, and by empirically identifying hidden utility level parameters through a structural model approach.

Research Context and Data

Our data are from a TNC. Its app has an ideal structure for studying the attribute value of the app. There is no new taxi introduced by the app, and all app users on the supply side are traditional taxi drivers. This setting helps to control the effects of car and driver characteristics. The only exogenous changes in the setting are the introduction of the app and promotional activities associated with it. Each driver makes a decision of using the app or traditional taxi business model in each period when his/her taxi is in vacancy.

In addition, the sample we analyzed is from a city where the supply of taxi is significantly lower than the demand. Statistics shows that more than 500 people share a taxi in this city. This statistics is consistent with the popularity of the app. Based on user experiences in our sample, orders arrive every few minutes. This condition erases our concern about endogeneity due to omitted demand when we model drivers' decisions of taking the app orders or traditional orders.

Given the information above, the structure of using app in each transaction is very straightforward. It can be aggregated into 3 stages sequentially. Before it starts, the app provider announces the cash back plan to drivers and passengers. Similar to most of marketing campaign, plan for passengers will be totally public. While the plan for drivers is revealed to drivers only through app, which allows more flexibility of policy changes. The plan for drivers and that for passengers are different and independent. In other words, drivers' information sets consist of cash back plans for drivers and for passengers, while passengers' are limited to plan for passengers only.

In the 1st stage, an order will be initiated by a passenger who needs a taxi. The passenger inputs the information of current location and destination. Usually this step is automatically filled by GPS and voice messages. After that, the passenger can type in the reward to the driver to increase the success rate. This reward will be paid by the passenger independently and added other than cash back and the regular fare. The request will be sent upon the completion of those inputs. It is sent to all available and nearby drivers.

In the 2nd stage, drivers will decide on whether accept an order from app or not, given the information of the location and destination, reward and expected cash back bonus from app. If a driver fulfills the order from app, he/she would certainly gain the regular fare and passenger reward, and gain app bonus conditional on whether the passenger pays online. If not, the driver would receive other form of order from other resources, e.g. roadside taxi takers or orders from call center, or waiting for the next order from any source. It is worth noticing that app-based orders are not necessary superior to regular orders. Even though drivers can get extra benefits from passenger reward and potential cash back from online pay, other than the regular fare, they also incur extra cost. One example is that drivers need to drive to the on-call location of passengers, which incurs operating cost, e.g. gasoline, if they take the order from online pay. While if they take order from roadside passengers, airport or hotel, the drivers does not incur such cost. This form of cost will be partially identified when the passenger cancels the order after a driver accepts it. In this case, drivers pay partial cost of operating gasoline and working time in order to fulfill the order, while not receive the benefit finally. Another example is some attribute cost of using app. For example, drivers need to install the app and pay more attention to app calling. This cost is bundled with the benefit of using app, such as giving information about the location and destination such that drivers can optimize route.

If drivers accept orders from app, passengers have two decisions to make in the 3rd stage. The first decision is whether to commit to the order accepted by a driver or not. In other words, the passenger still has chance to cancel the order. This case would happen if a passenger can get another format of transportation such as regular taxis or buses during the time while he/she is waiting. By taking outside alternatives, he/she would gain instant gratification and save reward promised to the driver, while giving up the potential cash back. The second decision is to pay online or not conditional on the delivery is completed. Passengers will gain cash back bonus based on policy if they pay online. Paying online also

incurs attribute utility such as convenience to pay. But attribute utility might be negative if function is hard to use, unstable or has a high failure rate.

We collect a dataset in a panel structure of a fixed subset of taxi drivers in the TNC firm. Our data sample s a fixed number of app users from the TNC platform, and we keep track of all the transactions of the subset of drivers since their registration. We give up the extremely sparse observations during the initial demo period of the app, and start our observation close to the release date of full version of the app, when all major functions are included, such that we take the attribute value, in other words, the aggregate function of characteristics of the app, as stationary. In total, we have around 26000 transactions. We observe the following 7 variables: whether drivers accept the orders, whether transactions are successful, whether online pay is used, cash back for passengers when use online pay, cash back for drivers when passengers use online pay, reward from passenger, and reward from TNC. Those data, in general, record the business process and the richness of sales promotion TNC used.
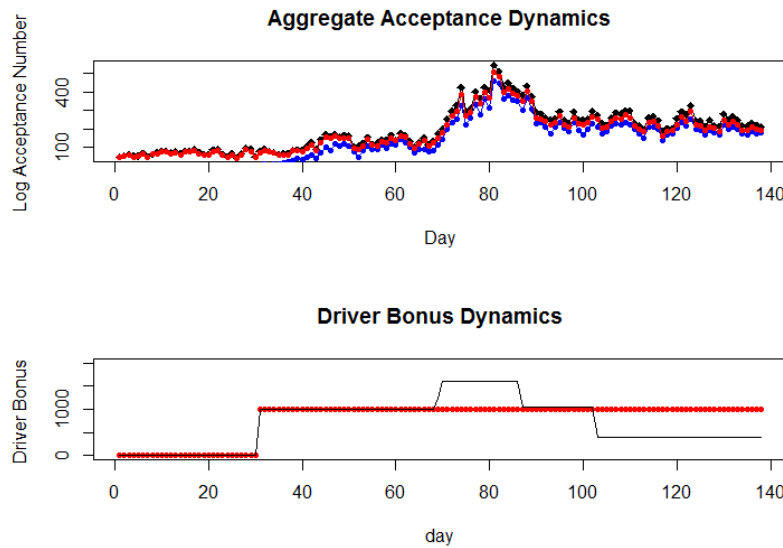

Figure 1

Figure 1 shows daily aggregate level transaction amounts and daily promotion policy from the app provider. In aggregate acceptance dynamics, black dots represent daily acceptance count, blue dots represent daily online payment count, and red dots show daily successful transaction count. In general, usage of online payment and successful transactions are proportional to the accepted amounts. In the driver bonus dynamics chart, cash back promotion policy changes with time. It starts from day 30 with a constant level for taxi drivers. For customers, it also starts on day 30, and goes up on day 70, goes down on day 85, and goes down again on day 100. It is very significant that transaction amounts increase when promotion is high, which confirms the existence of direct effect. Furthermore, it is shown that the total accepted amounts per day is more consistent with customer cash back amounts, which indicates that drivers' decisions of accepting an order is not only conditional on drivers' cash back policy, but also customers'.

The graph also shows that there is a very intensive peak of promotion between day 70 and day 90. During this period, drivers accumulate users' experiences intensively. Comparing aggregate acceptance between day 30 to day 70, with that between day 90 to day 100, we find that even promotion policy for both sides are the same in those two periods, after the intensive promotion of the peak, the same promotion policy can generate more accepted orders (between day 90 and day 100) than that generated before the peak (day 30 to day 70). This phenomenon indicates that drivers' willingness to accept orders increase significantly by promotion peak. And one reasonable explanation for the increment might be that intensive users' experiences lead drivers fully perceive the value of App, such that they are converted to be frequent users.

Model

Driver makes decisions on whether to us app to receive orders or to use natural passenger resource to receive orders, e.g. phone call, airport pickup, hotel pickup, passengers on the roadside, etc. We assume a driver i at time t will receive utility of U_{lit}^{a} if he/she accepts order from taxi app, and U_{0it}^{a} if not.

Two possible outcomes will occur after the driver accepts the offer from app. If a passenger is committed to the order, the transaction will be successful and the driver would gain positive utility from using app. If the passenger cancels the current order, the transaction fails, the driver incurs opportunity cost in terms of time or gas, as negative utility. By using an indication function, we can form the utility as following.

$$U_{1it}^{a} = D_{it}^{s} \times U_{1it}^{suc} + (1 - D_{it}^{s}) \times U_{1it}^{fail} + \varepsilon_{1it}^{a}$$

Here D_{it}^{s} is a dummy variable indicating whether transaction is successful, U_{1it}^{suc} is the utility if the transaction is successful, which is expected to be positive. And U_{1it}^{fail} is the utility if the transaction fails, which is expected to be negative. ε_{1it}^{a} represents the exogenous shock, which follows type I extreme distribution.

More specifically, when transaction is successful, drivers gain utility from the attribute of the app and all forms of bonus. There are three formats of bonus for taxi drivers. First one is cash back bonus if a passenger uses online payment. Second one is passenger reward, which increases drivers' incentive to accept a certain order, and is known before the driver makes decision. Third term is driver subsidy. It is similar to passenger reward, but it is from the app provider. We use additive form with scalars for attribute and monetary unit of bonus.

$$U_{1it}^{suc} = a_1 \times A_{it} + a_2 (D_{it}^{P} \times B_{it}^{cb} + B_{it}^{tip} + B_{it}^{sub})$$

Here, A_{it} represents utility from attribute of app. D_{it}^{P} is a dummy variable indicating whether passengers use online payment. B_{it}^{cb} represents the bonus cash back for drivers from app providers when online payment is used. B_{it}^{tip} is reward from passengers and B_{it}^{sub} is the subsidy from app provider.

When transaction fails, we simply take the value of utility as a constant number C^{fail}, which is expected to be negative. The constant should be the expected cost of gas for picking up the passenger. We model it as a constant since it is different across different formats of orders. And those time-varying random terms are the same across order formats, such can be cancelled out. Take both cases together, we have utility of accepting the order as the following expression.

$$U_{1it}^{a} = D_{it}^{s} \times (a_1 \times A_{it} + a_2 (D_{it}^{P} \times B_{it}^{cb} + B_{it}^{tip} + B_{it}^{sub})) + (1 - D_{it}^{s}) \times C^{fail} + \varepsilon_{1it}^{a}$$

At time t, if taxi the driver i receives utility from outside goods, he/she receives utility of U_{0it}^{a}. We take the utility from outside goods to be an attribute level C^{out} plus a stochastic error term.

$$U_{0it}^{a} = C^{out} + \varepsilon_{0it}^{a}$$

Before drivers make decision on whether using app to receive orders, they form expectation of the utility from 2 channels based on information updated to period t, and pick the channel which maximizes their instant expected utility. Before expectation forms, policy of cash back bonus for drivers and passengers, app subsidy and consumer reward are known. Other than the 3 formats of cash back or rewards we mentioned above, there is one more format of sales promotion for passengers, which is the cashback promotion provided by TNC to passengers. We denote it as C_{it}^{cb}. In addition, information till time t,

represented by I_{it} is known. By taking expectation conditional on known information, and rearranging our expected utility function by linearity of conditional expectation, we have following expressions

$$E(U_{1it}^a \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = a_1 \times E(A_{it} \times D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})$$

$$+a_2 \times E(D_{it}^P \times B_{it}^{cb} \times D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) + a_2 \times E(B_{it}^{tip} \times D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})$$

$$+a_2 \times E(B_{it}^{sub} \times D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) + (1 - \Pr(D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})) \times C^{fail} + \varepsilon_{1it}^a$$

$$E(U_{0it}^a \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = E(C^{out} \mid I_{it}) + \varepsilon_{0it}^a$$

Expected utility of outside goods is assumed to be stable since all drivers is experienced and well informed of the value of outside goods.

$$E(U_{0it}^a \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = C^{out} + \varepsilon_{0it}^a$$

As B_{it}^{tip}, B_{it}^{cb} and B_{it}^{sub} are given before forming expectation, these three terms can be taken out of the expectation form. In addition, we note that the perception of attribute by drivers is independent from the decision of commitment to an order by a passenger. So by some rearrange following the property of conditional expectation, we have the following expression.

$$E(U_{1it}^a \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = \Pr(D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) \times (a_1 \times E(A_{it} \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}))$$

$$+a_2 (\Pr(D_{it}^P \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, D_{it}^s, I_{it}) \times B_{it}^{cb} + B_{it}^{tip} + B_{it}^{sub}))$$

$$+(1 - \Pr(D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})) \times C^{fail} + \varepsilon_{1it}^a$$

On the expression above, drivers need to perceive three expectations. First one is expected value of attribute, which is $E(A_{it} \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})$. Second one is the probability of receiving committed order, which is $\Pr(D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})$. Third one is the probability that a passenger will pay online, which is $\Pr(D_{it}^P \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, D_{it}^s, I_{it})$. All three terms are conditional on users' experience. We explain the formation of these three expectations separately and then merge them together into our utility function to form likelihood.

Expected Attribute Level

We use Bayesian updating rule to model perceived attribute level. At the beginning of our observation, the driver has prior perceived value of app as A_{it}, which follows $N(A_0, \sigma_{A0}^2)$. It follows normal distribution, because the driver is uncertain about the app value, and σ_{A0}^2 captures the uncertainty level which is comparably large, whereas A_0 measures the mean level of the prior perceived value. The driver makes first time decision based on prior information only, such that mean of first time perceived attribute is equal to the prior mean value A_0, and the perception of variance is equal to σ_{A0}^2. As passenger learning about attribute is conditional on experience only, we use $E(A_{it} \mid I_{i0})$ to replace $E(A_{it} \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})$ for simplicity.

$$E(A_{it} \mid I_{i0}) = A_0$$

$$\sigma_{Ai0}^2 = \sigma_{A0}^2$$

Here σ_{Ai0}^2 is the variance of a driver's perception of mean attribute level at the very beginning.

Drivers updates perceived value and variance when they are better informed and when they learn the real attribute value of app. We assume the experience signal of app's true value A_{it}^e follows $N(A_1, \sigma_{A1}^2)$. A_1 is the average experience value which equals true value, and σ_{A1}^2 captures variance of signal. With more exposure to using app, driver's perceived attribute value will be driven from prior value and finally converges around the true value. Also the uncertainty about attribute value declines, and perceived variance becomes smaller. Such serial changes in perceived value can be modelled through Bayesian updating rule, which depicts a concave learning curve from prior mean and converges at true value, with the curvature governed by σ_{A0}^2 and σ_{A1}^2. Using a dummy variable D_{it}^a to capture whether driver i uses the app at time t, we can model our perceived attribute level and variance as follows.

$$E(A_{it} \mid I_{it}) = D_{it}^a \times \frac{\dfrac{A_{it}^e}{\sigma_{A1}^2} + \dfrac{E(A_{i1(t-1)} \mid I_{i(t-1)})}{\sigma_{Ai(t-1)}^2}}{\dfrac{1}{\sigma_{A1}^2} + \dfrac{1}{\sigma_{Ai(t-1)}^2}} + (1 - D_{it}^a) \times E(A_{i1(t-1)} \mid I_{i(t-1)})$$

$$\sigma_{Ait}^2 = D_{it}^a \times \frac{1}{\dfrac{1}{\sigma_{A1}^2} + \dfrac{1}{\sigma_{Ai(t-1)}^2}} + (1 - D_{it}^a) * \sigma_{Ai(t-1)}^2$$

Probability of Receiving Committed Order

Commitment to a proposed order is the decision of a passenger. Drivers learn about decisions of passengers through experience, and form expectation over the decisions to calculate their expected utility. In other words, We assume that driver have a constant belief about the attribute of cancelling order, however, due to the fact that such function is newly introduced, drivers would need to take some time to figure out this value. Even drivers know $B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}$ and B_{it}^{sub}, passengers' knowledge set is limited to C_{it}^{cb}, cash back they gain if they pay online, B_{it}^{tip}, the reward they give driver to increase the accepting rate, and the attribute level of committing to an order. In other word, drivers know that B_{it}^{cb} and B_{it}^{sub} are independent on the probability of a successful transaction. So drivers' belief in utility of passengers is conditional on $C_{it}^{cb}, B_{it}^{sub}$ and information till time t. We can simplify the expression as follows by pulling out independent variables.

$$E(U_{0it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = E(U_{0it}^s \mid C_{it}^{cb}, B_{it}^{tip}, I_{it})$$

$$E(U_{1it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = E(U_{1it}^s \mid C_{it}^{cb}, B_{it}^{tip}, I_{it})$$

$$\Pr(D_{it}^s \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = \Pr(D_{it}^s \mid C_{it}^{cb}, B_{it}^{tip}, I_{it})$$

We assume that in drivers' perspective, passengers gain constant utility plus exogenous shock when abandoning current app order and take alternative transportation in outside goods pool, for example, regular taxis or other transportation forms. As drivers are used to traditional transportation forms, they are well informed about the systematic component of utility for passengers. We thus model it as a constant.

$$E(U_{0it}^s \mid C_{it}^{cb}, B_{it}^{tip}, I_{it}) = C^s + \varepsilon_{0it}^s$$

If passengers are willing to wait, drivers expect passengers gain utility from three sources: attribute level for passengers to call taxis through app, cash back from app if they keep on using online payment, and paying extra reward. Among these three terms, C_{it}^{cb} and B_{it}^{sub} are known with certainty for drivers, and attribute is known by passengers but not fully known by drivers. Drivers need to learn about this value through their experience. Similar to part 4.1, we model these learning processes following Bayesian updating rule with prior perceived value following $N(S_0, \sigma_{s0}^2)$, and signal following $N(S_1, \sigma_{s1}^2)$. The perceived attribute value in time t for individual i is $E(S_{it} | C_{it}^{cb}, B_{it}^{tip}, I_{it})$. In terms of cash back, it is intuitive that the higher the cash back, the more expected utility for waiting. Notice that here, paying extra reward signals the high evaluation of a taxi, and might signal emergency for getting a taxi. It might be positively correlated with latent utility. However, it is extra cost for passengers, so it might be negative as well. Following these mechanisms, drivers form expected utility of drivers' willingness to wait based on information in passengers' information set. The latent utility follows the expression below.

$$E(U_{1it}^s | C_{it}^{cb}, B_{it}^{tip}, I_{it}) = d_1 \times B_{it}^{tip} + d_2 \times E(S_{it} | C_{it}^{cb}, B_{it}^{tip}, I_{it}) + d_3 \times C_{it}^{cb} + \varepsilon_{1it}^s$$

We simply model the probability of receiving commitment by assuming error follows extreme value distribution.

$$\Pr(D_{it}^s | C_{it}^{cb}, B_{it}^{tip}, I_{it}) = \frac{\exp(d_1 \times B_{it}^{cb} + d_2 \times E(S_{it} | I_{it}) + d_3 \times C_{it}^{cb})}{\exp(d_1 \times B_{it}^{tip} + d_2 \times E(S_{it} | I_{it}) + d_3 \times C_{it}^{cb}) + \exp(C^s)}$$

Probability of Online Pay

Bonus can be given if passengers decide to use online payment function to deal with fare. Similar to the decision of making transaction successful, it is a decision of a passenger but we model it in drivers' perspective such that we can incorporate it into drivers' expected utility. Notice that if a transaction is reported as online payment, it indicates a successful transaction. We simply model a conditional event on committed transaction by using subsetted data that are committed.

Similar to a driver's learning about probability of a successful transaction, consumer's information set is limited to C_{it}^{tip}, B_{it}^{tip} and attribute level of using online pay.

$$E(U_{0it}^P | D_{it}^s, B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = E(U_{0it}^P | D_{it}^s, C_{it}^{cb}, B_{it}^{tip}, I_{it})$$

$$E(U_{1it}^P | D_{it}^s, B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = E(U_{1it}^P | D_{it}^s, C_{it}^{cb}, B_{it}^{tip}, I_{it})$$

$$\Pr(D_{it}^P | D_{it}^s, B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = \Pr(D_{it}^P | D_{it}^s, C_{it}^{cb}, B_{it}^{tip}, I_{it})$$

Drivers are well informed of passengers' gain from outside goods utility when they pay by cash or use alternative transportation methods, because both drivers and passengers are used to traditional payment or transportation. We assume utility is summation of a constant and exogenous shock.

$$E(U_{0it}^P | D_{it}^s, C_{it}^{cb}, B_{it}^{tip}, I_{it}) = C^P + \varepsilon_{0it}^P$$

Drivers also know that passengers receive utility for attribute of online payment when passengers pay online, promotional cash back from the app, and paying for tips (rewards) depending on their willingness. Again we model attribute level following Bayesian updating rule with prior following $N(P_0, \sigma_{p0}^2)$ and signal following $N(P_1, \sigma_{p1}^2)$. Cash back is given conditional on passengers' usage of online payment, such that it is a strong incentive for preference of online payment when cash back is high. Reward can incur cost for passengers, such that it is negatively related to the joint event of successful transactions and pay online.

Following mechanism above, we model drivers' belief in utility of passengers when they pay online as follows.

$$E(U_{1it}^{p} \mid D_{it}^{s}, C_{it}^{cb}, B_{it}^{tip}, I_{it}) = b_1 \times C_{it}^{cb} + b_2 \times E(P_{it} \mid I_{it}) + b_3 \times B_{it}^{tip} + \varepsilon_{1it}^{P}$$

The perceived probability that passenger jointly make successful transactions and use online pay follows the expression as we assume error term follows extreme value distribution.

$$\Pr(D_{it}^{P} \mid D_{it}^{s}, C_{it}^{cb}, B_{it}^{tip}, I_{it}) = \frac{\exp(b_1 \times C_{it}^{cb} + b_2 \times E(P_{it} \mid I_{it}) + b_3 \times B_{it}^{tip})}{\exp(b_1 \times C_{it}^{cb} + b_2 \times E(P_{it} \mid I_{it}) + b_3 \times B_{it}^{tip}) + \exp(C^{P})}$$

We form our probability of pay online conditional on successful transaction and information up to time t based on rule for conditional probability.

$$\Pr(D_{it}^{P} \mid D_{it}^{s}, C_{it}^{cb}, B_{it}^{tip}, I_{it}) = \frac{\Pr(D_{it}^{P}, D_{it}^{s} \mid C_{it}^{cb}, B_{it}^{tip}, I_{it})}{\Pr(D_{it}^{s} \mid C_{it}^{cb}, B_{it}^{tip}, I_{it})}$$

Probability of Accepting Order

We plug in the result above into the expected utility when drivers use the TNC app. Using D_{it}^{a} as a dummy variable indicating the driver i accepts an order at time t if $D_{it}^{a} = 1$, we can form a likelihood as follows.

$$\Pr(D_{it}^{a} \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}) = \exp(\Pr(D_{it}^{s} \mid C_{it}^{cb}, B_{it}^{sub}, I_{it}) \times (a_1 \times E(A_{it} \mid I_{it})$$

$$+ a_2(\Pr(D_{it}^{P} \mid D_{it}^{s}, C_{it}^{cb}, B_{it}^{tip}, I_{it}) \times B_{it}^{cb} + B_{it}^{tip} + B_{it}^{sub})) + (1 - \Pr(D_{it}^{s} \mid C_{it}^{cb}, B_{it}^{sub}, I_{it})) \times C^{fail})$$

$$/(\exp(C^{out}) + \exp(\Pr(D_{it}^{s} \mid C_{it}^{cb}, B_{it}^{sub}, I_{it}) \times (a_1 \times E(A_{it} \mid I_{it}) + a_2(\Pr(D_{it}^{P} \mid D_{it}^{s}, C_{it}^{cb}, B_{it}^{sub}, I_{it}) \times B_{it}^{cb}$$

$$+ B_{it}^{tip} + B_{it}^{sub})) + (1 - \Pr(D_{it}^{s} \mid C_{it}^{cb}, B_{it}^{sub}, I_{it})) \times C^{fail}))$$

$$Llik = \prod_{i=1}^{I} \prod_{t=1}^{T_i} \Pr(D_{it}^{a} \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it})^{D_{it}^{a}} \times (1 - \Pr(D_{it}^{a} \mid B_{it}^{cb}, C_{it}^{cb}, B_{it}^{tip}, B_{it}^{sub}, I_{it}))^{1 - D_{it}^{a}}$$

Estimation Result

The identification of our model is very intuitive. Due to the fact that only difference matters in discrete choice model, among true attribute value, prior attribute value and constant terms in each Bayesian updating process, only two of them can be identified. A very detailed explanation of Bayesian learning model can be found in Crawford and Shum (2005). Since we are more interested in difference between true attribute value and prior one, and we want to test whether the true attribute value is higher or lower than the prior attribute value, we simply fix true attribute value at zero and leave prior attribute value and constant with freedom. Only the difference between prior and true attribute value makes sense. This is also the most computationally savvy way for minimization algorithm.

We use the simulated MLE method to recover parameter by following 2-stages estimation. On stage 1, we recover parameters in model Probability of Online Pay and Probability of Receiving Committed Order. On stage 2, we simulate data from recovered parameters in stage 1, and estimate all the rest parameters in Probability of Accepting Order. Since our dependent variable is discrete choice variable, here we show the

goodness of fit by plotting the aggregate rate of dependent variable across different individuals for the same cumulative number of transaction in Figure 2.
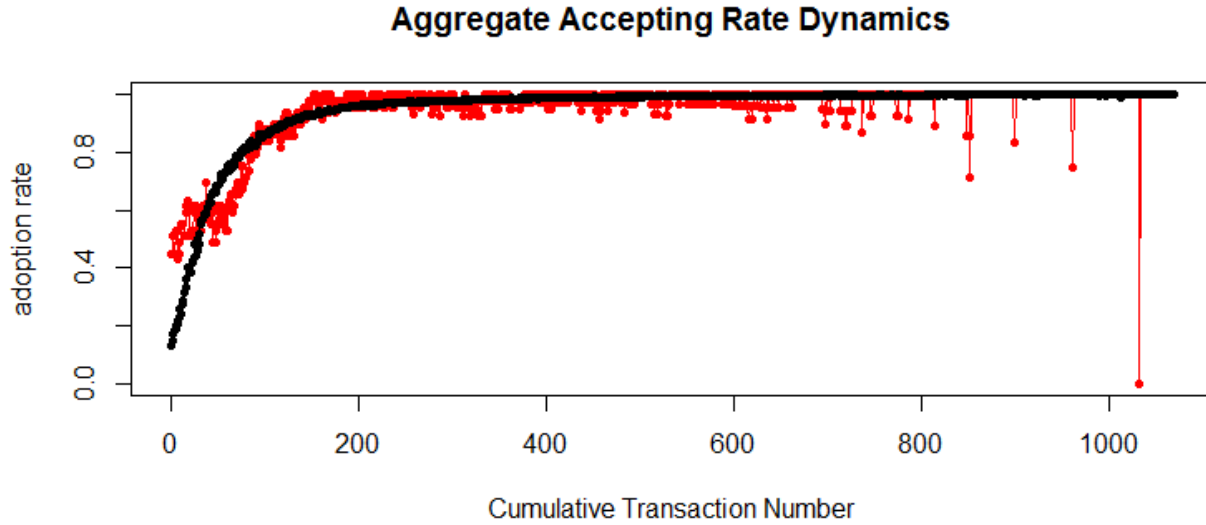
Aggregate Accepting Rate Dynamics

Figure 2

Our result shows several interesting findings. We find that the learning process exists in all three expectations. The prior for app attribute is negative, which indicates undervaluation of TNC app by drivers at the very beginning. The prior for app attribute value for committed customers is positive, which indicates that the successful rate is overvalued. The reason might be that there is no such function of cancelling an order in traditional taxi business model. When passengers catch taxis, it is very unlikely that they would leave and cancel the transaction. When cancelling function is implemented in TNC app, drivers would set prior based on their past experiences when they use traditional business model. The prior of online pay is also negative, which indicates its undervaluation as well. We also note that all signal variances are pretty large compared with the scale of attribute level. This indicates that signals through experiences are not informative and accurate. Drivers need to use it with comparably large quantity of experience to finally learn those attribute values.

Parameter	Estimate	S.E
P_0	-5.9385	0.47246
P_1	0	-
σ^2_{p0}	10	-
$\log(\sigma^2_{p1})$	3.5364	0.14884
b_1 (customer bonus)	0.4107	0.08381
$\log(b_2)$ (attribute learning)	-0.3084	0.08578
b_3 (consumer reward)	-2.5314	0.14877
C^P	- 1.8649	0.05464

Stage 1

Parameter	Estimate	S.E
S_0	0.9981	0.42240
S_1	0	-
σ_{s0}^2	10	-
$\log(\sigma_{s1}^2)$	6.5127	0.77111
d_1 (customer reward)	-0.3060	0.19091
$\log(d_2)$ (attribute learning)	-1.0228	0.20579
d_3 (customer cashback)	0.2525	0.08634
C^S	-2.1165	0.07636

Stage 2

Parameter	Estimate	S.E
A_0	-4.2214	0.19886
A_1	0	-
σ_{A0}^2	10	-
$\log(\sigma_{A1}^2)$	4.3679	0.08941
$\log(a_1)$ (attribute learning)	0.5600	0.04569
a_2 (monetary scalar)	0.6866	0.06266
C^{out}	-5.9309	0.158334
C^{fail}	-23.7650	1.02359

Stage 3

Table 1

We also identify parameters for two-sided promotion. Three forms of monetary bonus for drivers have positive effects on drivers' decision of adoption as expected. Furthermore, bonus policy for customers also has impact on drivers' decision through probability of receiving committed orders and probability of online pay. When cash back for consumers is high, both of above probabilities tend to be high, which increases latent utility for drivers to accept app based orders.

The thing worth noting is the consumer reward term. Though higher amount of consumer reward increases drivers' bonus earning, it decreases both of probability of receiving committed order and probability of online pay, which lowers drivers' utility. If a passenger commits to a higher tip, it indicates a higher charge for an app generated order. However, there is no commitment to outside goods simultaneously, such that he/she would definitely prefer outside goods if outside one is available. In terms

of the probability of online pay, a passenger who is willing to pay for higher tips is simply less sensitive to sales promotion, such that the willingness to use online pay is lower.

In addition, we find that all of app-based attribute have positive value. By fixing all of signal mean as 0, we infer attribute value through relative value to outside goods. We find that outside goods have constant negative utility, which indicates attribute utility of app is higher than utility derived from outside goods. Similar findings also apply to attribute level of using online pay, and attribute value of committing to an order. We also identify a large negative parameter for uncommitted transactions. This indicates that cancelling order hurts drivers as well as utility significantly, and might drive them to take outside goods.

Policy Simulation

We conduct two sets of policy simulation here to understand the impact of two-sided promotion on driver's order accepting rate. In the first set of policy simulation, we try to tease out the indirect effect from direct effect. In the second set of policy simulation, we modify several different cash back policies based on implication from our model-free evidence and estimation result. Our objective is to find a policy that keeps the acceptance rate the same while being more cost savvy for App provider.

We use our conditional Bayesian learning model to simulate the decision of accepting of a driver, whether the transaction is fulfilled, and whether driver receives cash back bonus. Specifically based on our conditional Bayesian model, in each loop, we firstly use updated believes of the probability that passengers will use onlinepay conditional on the transaction is fulfilled and of the probability that passengers will fulfill the order conditional on driver will accept the order to simulate driver's decision of accepting the order. Then we simulate whether the transaction is indeed fulfilled and whether the transaction is ended with onlinepay. Then we update perceived value of three kinds of attributes by using Bayesian learning, and use the updated belief in next time period. We simulate each policy for 100 times, and take the average as our result.

Estimating Indirect Effect of Sales Promotion

Indirect effect of sales promotion is implicitly proved by the existence of learning of driver in our model indicates. However, such effect is hard to measure directly by estimated parameters. We conduct a set of simulation here to show explicitly how much impact such effect exists for driver's decision. We firstly simulate a baseline of driver's decision across time period. By identifying a benchmark point in time horizon that accepting rate is stationary afterwards, which indicate that perceived value is converged with true value from that point, we simulate another case with removal of promotion policy from the benchmark point. Lastly, we simulate the third case with removal of promotion from the very beginning.
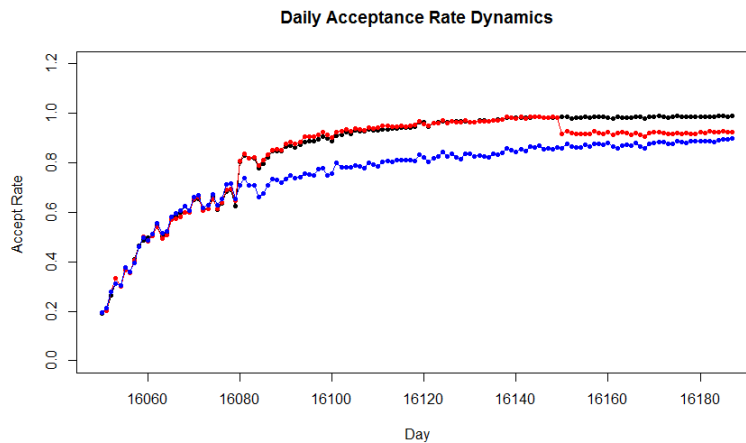

Figure 3

We aggregate the acceptance in daily level and show our result in figure 2. In the baseline case (Black), due to the fact that promotion exists from a middle day to the end, both direct effect and indirect effect exists at the end. The red line represents the case sales promotion ends on benchmark point. Accepting rate of driver is stationary from that point in both of black line and red line, indicating that drivers' perceived attribute value is consistent with true value. The difference between red line and base line is only resulted from the direct effect of sales promotion. Blue line has no sales promotion from the beginning of our observation. When we look at the end of our window, even though sales promotions are removed in both of red line and blue line, there is still significant discrepancy. As we can tell, blue line is still following an increasing pattern, which indicates that drivers are still learning about the true attribute value of app. Since there are no direct effect in both of blue line and red line case, this discrepancy can be explained as indirect effect of sales promotion through learning.

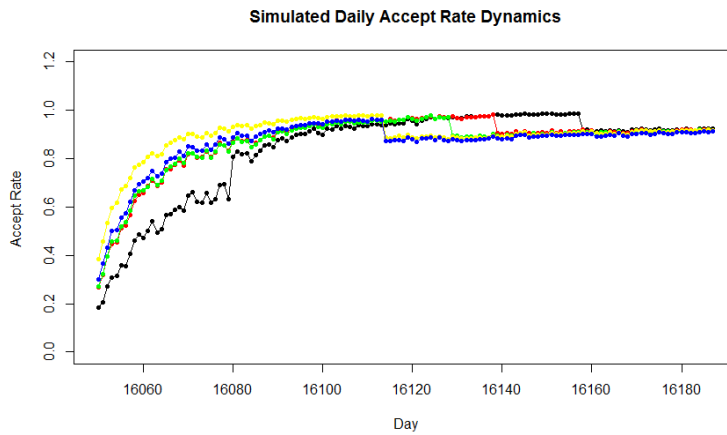## *Modification of Sales Promotion*

Figure 4

Even we identified the indirect effect of sales promotion in TNC setting; the efficiency of current policy in fostering driver's adoption rate is still under doubt. Given that current policy have already make drivers fully perceive attribute value from a certain point, question for efficiency mainly focus on whether such policy is cost savvy? Is there other policy more cost savvy for TNC while also help drivers to reach the stationary accepting rate after promotion ends? We conduct several modified sales promotion policy based on our estimation result, and find that we can at least save more than 50% of sales promotion investment for TNC if we improve the efficiency of such policy.

We use the blue line case in the first part of counterfactual as our baseline. We use this case because our goal is to at least keep the same accepting rate after benchmark point where all sales promotions are removed. In figure3, we use black line to represent the baseline. This policy actually incurs cost of more than $1, 200 per driver.

First new policy is simply to start our promotion earlier for both passengers and drivers, while keeping the amount the same (Red line). By starting earlier, we can enhance drivers' use experience earlier. Due to the general increasing trend of transaction amount per day as drivers uses more when learn more, period from the starting points actually have the fewest transaction amount, while incurred the most steep learning rate. It is obvious that it reach the same stationary accepting rate level at the end. Due to the decrease of transaction amount, our final cost for TNC is around $1,000 per driver, which means that cumulative sales promotion for passengers and drivers is about 16% fewer.

Our second policy further reduces the length of promotion by 10 days for both sides of passengers and drivers with the same starting point and the same promotion amount in red line case (Green line). We propose this policy because the red case shows that our accepting rate also converges at stationary level with promotion earlier when start earlier. It shows that it also reaches the stationary level once all promotions are removed earlier.   Since we remove sale promotions in period where most condensed mass of transaction amount lies in, such policy result in a cost of $700 per driver, which is significantly lower than red line. This policy achieves the same level of learning, while cutting almost half of sales promotion for passengers and drivers.

Our third policy is "more intensive for shorter period" (Yellow line). Since a tried policy only with furtherly shortened promotion doesn't reach the stationary level, we increase the amount of cash back for both drivers and passengers to encourage drivers to learn about the app more intensively. Our result shows that when we give customer cashback bonus at the maximal level of existed policy for all the time, and give 180% times of cash back for drivers, we reach the stationary point. Due to the increase amount for cash back, our cost saving is limited. Compared with last policy, we only save $20 per driver further. If we just increase the amount of cash back for customer at the maximal level (Blue line), it saves us $200 more than green policy, and our result is very close to stationary level.

Such findings actually explain why lots of industry TNC companies set intensive sales promotion. By setting more intensive sales promotion for shorter period, it actually saves promotion for later period when most mass lies in. The resulting total cost, though not necessary, might be even less than the alternative with less intensity but longer duration.

Conclusion and Implications

In short, our analysis of TNC app yields several findings. We generally identify the economics mechanism behind drivers' preferences for app-based orders versus outside goods. The recovered parameters have implications for app providers in industry. We find that TNC app generates value for users, while such value can be fully delivered through comparably heavy user experiences. This indicates app providers need to promote such app heavily at the very beginning stage, such that users would perceive value more quickly. However, such promotion can also help drivers realize the issue of cancelled orders, which drives drivers to outside goods. App providers should consider mechanism to decrease the cancellation rate.

In terms of two-sided promotion policy, as we mentioned in the result, both two sides of promotion have impact on drivers' propensity to join with different weights. App providers also need to pay attention to trade-off of consumer reward, as this term has negative direction effects on drivers' decisions.

The limitation of our paper lies in the homogeneity of our transaction data. Due to the fact that sales promotion is known and fixed for a long time horizon, and we have no access to transaction specific information, we actually model the orders as "homogenous" across time interval, which means that taxi driver takes order now or later have no states change. This limitation impedes us from discovering the forward-looking behavior of drivers. A future extension with more comprehensive data will be very interesting.

References

Arcidiacono, Peter. "Affirmative action in higher education: How do admission and financial aid rules affect future earnings?." *Econometrica* 73.5 (2005): 1477-1524.

Chen, Tao, Baohong Sun, and Vishal Singh. "An empirical investigation of the dynamic effect of marlboro's permanent pricing shift." *Marketing Science* 28.4 (2009): 740-758.

Chunhua Wu, Hai Che, Tat Y. Chan and Xianghua Lu (2015), "The Economic Value of Online Reviews," Marketing Science , forthcoming.

Crawford, Gregory S., and Matthew Shum. "Uncertainty and learning in pharmaceutical demand." Econometrica 73.4 (2005): 1137-1173.

"Decision Adopting Rules and Regulations to Protect Public Safety While Allowing New Entrants to the Transportation Industry". California Public Utilities Commission. Retrieved 26 Nov 2013.

Erdem, Tülin, and Baohong Sun. "An empirical investigation of the spillover effects of advertising and sales promotions in umbrella branding." *Journal of Marketing Research* 39.4 (2002): 408-420

Erdem, Tülin, and Michael P. Keane. "Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets." Marketing science 15.1 (1996): 1-20

Erdem, Tülin, Michael P. Keane, and Baohong Sun. "A dynamic model of brand choice when price and advertising signal product quality." Marketing Science27.6 (2008): 1111-1125.

Ghose, Anindya, and Sang Pil Han. "An empirical analysis of user content generation and usage behavior on the mobile Internet." Management Science57.9 (2011): 1671-1691.

Hamilton, C. A., et al. "Uterine papillary serous and clear cell carcinomas predict for poorer survival compared to grade 3 endometrioid corpus cancers."British journal of cancer 94.5 (2006): 642-646.

Huang, Yan, Param Vir Singh, and Kannan Srinivasan. "Crowdsourcing new product ideas under consumer learning." Management Science 60.9 (2014): 2138-2159.

Ho, Yi-Chun Chad, Yi-Jen Ian Ho, and Yong Tan. "Online Cashback Pricing: A New Affiliate Strategy for E-Business." Proceedings of the 34th International Conference on Information Systems (ICIS). 2013.

Li, Corinna, and Jinhua Zhao. "Humanizing Travel: How E-hail Apps Transform Stakeholder Relationships in the US Taxi Industry." *Transportation Research Board 94th Annual Meeting*. No. 15-0680. 2015.

Li, Ye, Tian Xia, and Hui Duan. "The Impact on Taxi Industry of Taxi-Calling Mobile Apps in Shanghai." *Transportation Research Board 93rd Annual Meeting*. No. 14-3867. 2014.

Osawa, J. (2015, February 13). Why China Taxi Apps Are Talking Merger. Retrieved March 26, 2015, from http://blogs.wsj.com/digits/2015/02/13/why-china-taxi-apps-are-talking-merger/

Rayle, Lisa, et al. "App-Based, On-Demand Ride Services: Comparing Taxi and Ridesourcing Trips and User Characteristics in San Francisco University of California Transportation Center (UCTC)." (2014).

Sugden, Joanna, Aditi Malhotra, and Douglas Macmillan. "Uber Under Attack Around the Globe." WSJ. 9 Dec. 2014. Web. 26 Mar. 2015. <http://www.wsj.com/articles/india-advises-all-states-to-ban-uber-and-other-car-hailing-services-14181 19647>.

Tan, Felix Ter Chian, Barney Tan, and Lesley Land. "The Affordance of Gamification in Enabling a Digital Disruptor: A Case Study of the goCatch Taxi Booking App."

Tangel, Andrew. "Ride-Sharing Service Lyft Defies New York City, State Regulators." The Wall Street Journal 10 July 2014. Web. 26 Mar. 2015. <http://www.wsj.com/articles/ride-sharing-service-lyft-defies-new-york-city-state-regulators-14050424 25>.

Zhao, Yi, et al. "Modeling consumer learning from online product reviews."Marketing science 32.1 (2013): 153-169.