Optimizing Two Sided Promotion for Transportation Network Companies: A Structural Model with Conditional Bayesian Learning

Abstract

Transportation network company app allows platform to run aggressive and diverse sales promotion to help introducing new product, while also incurs heavy cost for rewarding two sides of users. This paper addresses how two-sided sales promotion affects drivers’ willingness to use the transportation network company app, and how to form the optimal promotion strategies for the transportation network company. To investigate the effects of sales promotion, we estimate a structural model of decisions of accepting an order and that of cancelling generated orders by drivers. The model considers how drivers perceive passengers’ willingness to redeem sales promotion. Bayesian learning is introduced to account for decisions under uncertainty as the app product is newly introduced. We find measurable evidence of taxi drivers’ learning about attributes value of using transportation network app, indicating substantial value of promotion in early period since it not only encourages current usage, but also fosters learning that sustains drivers’ use afterwards. Our results also show that revealed tips from passengers signal low quality of orders, and platform cash back to passengers has positive effect on drivers by increasing drivers’ perceived chance of being rewarded. Given estimated parameters, we run simulations to explicitly measure indirect effect of sales promotion introduced by learning and show how cash back for passengers impacts decisions of drivers. Finally, our experimental sales promotion policies based on our model estimation results show improved performance with regard to drivers’ willingness to use while being more cost effective.

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

1. Introduction

Information system never stops its expedition into reshaping traditional business. One recent progress is “transportation network companies” (we use TNC interchangeably), which is defined as “a service that does not own vehicles or employ drivers, and relies on software to connect passengers to rides” (California Public Utilities Commission. Retrieved 26 Nov 2013). Early runners of transportation network app include well-funded firms, such as Uber, Lyft, Hailo, OlaCabs, and Didi Dache. Typical TNC 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 trips into the system to
personalize their orders, such as pickup location, destination and tips. Drivers can also personalize by picking an order which fits their latent priority scheme to optimize route and therefore profit.

Information system creates value for different parties of stakeholders through the following formats. For taxi drivers, TNC app provides extended features. For example, compared with traditional taxi drivers, TNC drivers extend passenger pool from hotline-reserved and eyesight-reached roadside passengers to a pool in which passengers can be miles away. Furthermore, taxi drivers can select passengers based on prior information about pickup location, destination, tips and other requirements to generally match their preferences of driving areas and routines. Those characteristics can be categorized as attributes value following Erdem et al. (2008).

Another revolutionary imbedded function of TNC app is allowing drivers to cancel an order with further information collected. Drivers might have different preferences across different formats of orders conditional on information and timing. In the traditional reservation-based transportation model, once a reservation is made, it incurs heavy cost if drivers change their minds. With cancelling function, drivers can easily adjust their preferences based on updated information about ordered TNC taxis through the app and instant information about outside goods from other channels such as roadside hailing.

For taxi passengers, TNC app provides value by simplicity and flexibility in transaction process. The most prominent function is online-pay, which enables passengers 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 when they receive email. It simplifies taxi riding business processes, and allows passengers to be reached by sales promotion easily and effectively, but might incur extra cost for drivers due to delayed gratification and extra steps of transaction by third party.

Another important role of TNC app is marketing campaigns to compete with the traditional transportation system. Promotion is a common practice in the industry during the introduction period of innovative online-to-offline experience goods. The app provides a platform on which release, implementation and adjustment of promotion can be conducted with ease. Individual-specific property allows targeted promotion for specific segment of users with well controlled timing and locations. In addition, more sophisticated but efficient marketing campaigns can be utilized to complement the introduction of app, or even a specific function of the app. One example is two-sided sales promotion. As two-sided market provides a platform which attracts both supply and demand, a two-sided sales promotion applies to both sides of market. Take taxi market as an example, during the period of sales promotion, both taxi drivers and passengers would enjoy cash back offer conditional on a fulfilled transaction with online-pay. It provides a flexible marketing mix for platform providers.
One typical challenge for TNC platforms is that potential users are less likely to switch to the new system due to their uncertainty about newly introduced features. A common practice shown in multiple industrial anecdotes overcoming this issue is to launch excessive sales promotion during the introduction period. The most recent example is that Uber raised one billion U.S. dollars to promote the adoption of Uber network in China, subsidizing new drivers as much as triple times of the regular fare per order. Other local firms as Didi and Kuaidi in China adopt similar strategies. Dated back earlier, Uber and Lyft in the U.S. paid drivers a 5 percent bonus for every ride they undertake during the introduction period. Industrial startups that run frequently purchased experience goods or services believe that it is worthy promoting to enhance usage experience for newly introduced product since usage experience would be converted to usage “habit”. More intensive promotion would accelerate usage experience of users through which users would be fully informed of attributes value of a new product. In other words, intensive sales promotion generates not only direct effect of instantly increased demand, but also indirect effect in long term, in which consumers fully perceive value of new products, becoming loyal more quickly, and purchasing the newly introduced product more frequently. This is consistent with consumer learning literature when prior of goods is undervalued; however, there is no academic literature systematically investigating and validating the effects of intensive promotion for two-sided online goods such as TNC app, which is the blank area we want to fill through this paper.

In this paper, we answer one set of questions: how two-sided sales promotion makes impact on drivers’ propensity to use TNC app? How two-sided sales promotion interacts with drivers’ learning dynamically? And how should we design a better promotion to accelerate drivers’ learning while being cost-effective. We focus on driver side of TNC platform because the market in our context as well as many other contexts is with excessive demand due to regulation, which makes supply side more crucial with respective to platform performance.

There are a number of challenges with measuring the effects of sales promotion for drivers. The first challenge arises from remodeled feature of business process such as cancelling and online-pay. It leads to a brand new business process which is never touched. It consists of sequential and connected decisions in each transaction, and sales promotion might have different effects in each decision. Effects happened in one stage decision might indirectly impact other stage decisions by the linkage among them. For example, a sales promotion policy in our data sample is that both drivers and passengers get cash back bonus when passengers use online-pay function. Therefore, an order with high potential to be redeemed with cash back by passengers will increase drivers’ willingness to accept and fulfill, since the expected profit would be higher. Without understanding the process of the multiple decision-making associated with the property of new features, it is impossible to quantify the effects of sales promotion accurately. Therefore, we build a
A structural model to explicitly recover the data generation process of drivers’ sequential decisions with the effects of sales promotion.

In addition, recall that sales promotion during the introductory period might have indirect effects due to diminishing uncertainty, our model needs to account for uncertainties for new features imbedded in different stages of decisions. A typical Bayesian learning model can handle this issue nicely; however, it is limited to learning of one attribute associated with one decision. In our case, each usage experience consists of attributes in multi-dimensional space with each dimension representing attribute for one stage decision. Given that the decisions are related to each other, the learnings associated with different decisions are also connected with each other. We accommodate our structural model with a Bayesian learning conditional on earlier stage decisions to model connected learning processes of drivers’ willingness to accept an app generated order, that to fulfill the order, and drivers’ belief of passengers’ willingness to use online-pay.

Using data from a leading TNC in China, our result quantifies drivers’ learning of using app to accept orders, that of using cancelling function, and drivers’ belief of how passengers learn about using online-pay. We find that tips from passengers, subsidies from app provider, cash back bonus for passengers and cash back bonus for drivers all affect drivers’ decisions through not only direct impact on latent utility of taxi drivers, but also drivers’ belief in passengers’ decisions of using online-pay and commitment to orders. Our counterfactual analysis separates learning induced indirect effect of sales promotion from the direct effect. It also identifies effects of sales promotion for passengers on drivers’ decision, and provides managerial implications for similar app providers about how to accelerate consumer learning while being cost-effective.

The rest of the paper is organized in the following way. In Section 2, we briefly talk about related literature and our contribution correspondingly. We describe the research context and available information from our dataset in Section 3. In Section 4, we present our model of drivers’ decision of using TNC app. In Section 5, we discuss our estimation strategy and report the estimation result. We simulate data to generate insights of our model and propose optimized sales promotion strategy in Section 6. Finally we summarize our findings and conclude our research in Section 7.

2. Literature Review

Our research is related to the literature dynamic between empirical consumer learning and sales promotion. A large quantity of industry anecdotes identify sales promotion in product introduction period as a strategy to enhance usage experiences and to foster consumer learning. However, in most research settings of experience goods with adequate variation of prices, sales promotion is limited in its direct effect, which is equivalent to temporary price cut. Consequently, very little academic research pays attention to teasing out indirect effect of sales promotion from the direct price effect. There are exceptions as Erdem and Sun (2002). In their research, they investigate and find evidence of spillover effects of sales
promotion and advertising in umbrella branding of multiple products. In Chen et al. (2009), it investigates 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 in e-business and generates richness of innovative marketing mix. Our counterfactual analysis brings insights of how to improve such promotion.

In methodology, our research applies Bayesian learning model to a finite-horizon forward-looking context. Erdem and Keane (1996) firstly identify consumer learning about product quality level through experience and unobserved signals like advertising by applying Bayesian updating process. Due to its applicability with consumers’ choices under uncertainty, learning model is widely extended to account for many formats of 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. 2015). 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. 2009). In information systems 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 et al. 2013). In our paper, we extend Bayesian learning model by accounting for learning about multiple attributes associated with conditional decisions, which fits our research context very well. To our knowledge, this is the first IS study using conditional Bayesian learning to address sequential decisions. To model sequential decisions, we follow Arcidiacono (2005) which investigates affirmative action’s effects on sequential decisions in higher education application.

Our paper is also the first study investigating micro level of on-demand TNC apps from information systems perspective. Even though TNC apps attract lots of attention in 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 taxi industry or public transportation system. Rayle et al. (2014) find that ride-sourcing complements traditional taxis and public transit by introducing younger passengers, 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 systems 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, none of prior literature has explained TNC app business model from micro level perspective as we do in this study. We model transactional level behavior of TNC app users and empirically identify hidden utility level parameters through a structural approach.

3. Research Context and Data

Our data is from a TNC in China. It is now the leading mobile-app-based transportation network in China with over 150 million registered passengers, 1.5 million registered taxi drivers and 5 million transactions per day.

The structure of this app is an ideal setting for studying the attributes value of app. Different from Uber who introduces more supply of transportation, this app only applies to existed taxis in the market due to the heavy regulation on taxi market. In other words, there is no new taxi introduced by the app, and all app users in supply side are traditional taxi drivers. This setting helps to control other effects such as car characteristics and driver characteristics, leaving the only exogenous changes as the introduction of the app and promotional activities with that. Each driver makes a decision of using app or using traditional taxi business model in each period when their taxis are in vacancy.

In addition, the sample we analyzed is from a city where the supply of taxi is extreme lower than demand. Statistics show a ratio of more than 500 people per taxi in this city. It is consistent with the popularity of the app. Based on usage experience in our sample, orders arrive every few minutes. This erases our concern about endogeneity due to omitted demand when we model drivers’ decisions of taking app orders or traditional orders.

From drivers’ perspective, each transaction involves three stages. Prior to stage 1, app provider announces cash back plans to drivers and passengers. Note that the policy is to give cash back to drivers and passengers only if passengers pay the fare online instead of cash. Similar to most marketing campaigns, cash back plan for passengers is totally public, but that for drivers is revealed to drivers only through app. In other words, drivers’ information set consists of cash back plans for drivers and that for passengers, while passengers’ is limited to plan for passengers only. Given the policy, an order will be initiated by passengers who need a taxi. Passengers input information of current location and destination. Usually this step is automatically filled by GPS and voice messages, which is unobservable to econometricians. Passengers could additionally reveal tips to corresponding drivers to increase the probability that their order would be accepted. After that, platform also reveals subsidy for drivers at a constant rate for several short terms regardless of whether paying online or order quality. Both tips and
subsidy would be revealed to drivers before they accept the order. This is different from traditional business model. Subsidies and tips will be paid independently and added to cash back and the regular fare. The order request will be sent upon the completion of those inputs. It is sent to all available and nearby drivers.

In stage 1, drivers will decide on whether to accept an order from app or not give information mentioned above. If a driver accepts an order from the app, he/she would certainly gain the regular fare, passenger tips and platform subsidy (if applicable), and cash back bonus conditional on passengers paying online. If not, the driver would take other forms of order from other sources, 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 necessarily superior to regular orders. Even though drivers can get extra benefits from monetary rewards as well as ease of use due to new features of the app, they also incur extra cost associated with new functions. One example is that drivers need to use third party financial service to process a transaction which inhibits instant gratification if passengers use online-pay. Another example is some attribute cost related to the use of the app such as drivers’ efforts to install the app and to pay more attention to app calling, and as the potential idle time during driving to pick up passengers.

Conditional on accepting an order, drivers decide whether to fulfill the order or cancel it during stage 2. This case would happen if drivers take orders as low quality or risky, or if superior alternative orders are available. The decision of cancelling an order looks homogenous to the decision of accepting an order; however, they are different in time space which indicates additional information that allows drivers for further action. In addition, cancelling is a new feature which never exists in the traditional taxi business model and introduces possibility of drivers’ new decision rule. An order taken as low quality or risky and be abandoned in traditional business model might be accepted first and cancelled later given more information revealed. This new feature might also introduce distinctive learning pattern.

Stage 3 is for decision of paying online or not by passengers conditional on ride is completed. Paying online might incur positive attribute such as convenience, as well as negative one like function is hard to use, unstable or has a high failure rate. To promote using online-pay, in our context cash back for both sides are contingent on this decision, implying that drivers will gain cash back bonus if passengers pay online. Even though it is not a decision of drivers, a rational driver would form belief about this decision since it matters with benefits for one specific transaction.

Rational drivers would be backward-looking and be forward-looking when use TNC apps. Backward-looking means that drivers would learn to use different functions associated with different stages from their usage experience. Each usage experience would signal drivers the attribute of specific function such that drivers will be more certain and less biased about using the app. Forward-looking, on the other hand, means drivers would decide on earlier stages based on his belief about potential outcomes
in later stages to optimize his overall utility. It makes decisions of different stages be connected and be unified.

We collect a panel structured data from the TNC firm. Our data samples 952 taxi drivers who have used the TNC app at least once during the introductory period, and we keep track of all the transactions of this set of drivers ever since their registration. In total, we have 198,689 transactional records. We observe the following seven variables: whether drivers accept the orders, whether transactions are fulfilled, whether online pay is used, cash back amount for passengers when use online-pay, cash back amount for drivers when passengers use online-pay, tips from passengers, and subsidies from TNC platform. This data, in general, records the business process and the richness of sales promotion by the TNC platform. We show summary statistics in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Stdev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceptance</td>
<td>0.7622</td>
<td>0.4963</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Fulfillment</td>
<td>0.6388</td>
<td>0.4803</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Online-Pay</td>
<td>0.4394</td>
<td>0.4257</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Cashback for Driver*</td>
<td>1.4733</td>
<td>0.3625</td>
<td>0</td>
<td>1.5625</td>
</tr>
<tr>
<td>Cashback for PSGR*</td>
<td>1.5843</td>
<td>0.6768</td>
<td>0</td>
<td>2.5000</td>
</tr>
<tr>
<td>PSGR Tips*</td>
<td>0.0076</td>
<td>0.1531</td>
<td>0</td>
<td>7.8125</td>
</tr>
<tr>
<td>Platform Subsidies*</td>
<td>0.0300</td>
<td>0.2149</td>
<td>0</td>
<td>15.6250</td>
</tr>
</tbody>
</table>

*The unit for currency is US dollar

To understand the effects of sales promotion and that of learning, we analyze daily aggregate level transaction amounts corresponding to daily promotion policies as Figure 1 shows. The time horizon in the figure is ranging three months in the introductory period of the app. In daily average outcomes, we visualize outcome variables with lines in black, red and blue to represent daily acceptance rate, daily fulfillment rate and daily online-pay rate respectively. In general, use of online-pay and fulfilled transactions are proportional to the accepted amounts with increasing trend over time. In sales promotion policy chart, cash back promotion policy also changes over time. For drivers it starts with 0, and maintains at a higher level from day 10. For passengers, it also starts with 0, and goes up from day 10 to day 70, and declines afterwards. Other rewards chart shows declining trend of tips from passengers and subsidies from platform.

There are several interesting findings by comparing outcome variables with respect to sales promotion policy. We find an overall increasing pattern of outcome with more intensive sales promotion, which indicates sales promotion stimulates acceptance rate, fulfillment rate and online-pay rate. In addition, we find that all of outcomes, including acceptance rate and fulfillment rate which are controlled by drivers, increase with the increment of cash back for passengers around day 50. It implies sales
promotion for passengers might have effects on decisions of drivers. Furthermore, comparing outcomes after day 70 with that before day 45, we find that even though sales promotion policy for both sides are almost the same, and tips from passengers and subsidies from platform are even higher during earlier period, more orders are accepted and fulfilled with online-pay after day 70. Considering the difference in contexts of those two periods, one possible explanation for the increment might be that usage experience accumulated between day 45 and day 70, which leads drivers to fully perceive the value of app and convert them to be frequent users. Similar finding could be found by dividing time horizon into three even periods and comparing average measurement of outcomes as shown in Table 2. Comparing the middle 30 days with the last 32 days, all of three outcome variables are improved with even declining in sales promotions and other rewards.

Figure 1. Sales Promotion vs. Outcome Variables Dynamics

4. Model

We present a structural model on data generation process of how typical orders on TNC app are accepted fulfilled and finished given requests from passengers. As we discussed, orders will go through three stages of decisions:

Stage 1 drivers decide whether to accept an order.

Stage 2 drivers decide whether to cancel an accepted order.
Stage 3 passengers decide whether to redeem sales promotion.

Note that drivers’ decisions in stage 1 are conditional on their believes on what will happen in stage 2 and stage 3, and so does decisions in stage 2 conditional on stage 3, the model needs to account for finite horizon forward looking dynamics. This requires us to model the decision preference while accounting for relation among different stages with decision dependent state transition. We model those decisions in a forward way for easier interpretation and estimate by following typical backward induction. Specifically, we subscript parameters associated with the decision of accepting an order with $a$, of fulfilling an accepted order with $s$, and of redeeming sales promotion with $c$ to avoid potential confusion. We define arrival of each order as one time period.

Table 2. Change Over Time

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Outcomes</th>
<th>Sales Promotion and Other Rewards</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#Orders</td>
<td>Accept</td>
</tr>
<tr>
<td>Overall</td>
<td>198689</td>
<td>0.76</td>
</tr>
<tr>
<td>First 30</td>
<td>56291</td>
<td>0.62</td>
</tr>
<tr>
<td>Mid 30</td>
<td>67259</td>
<td>0.77</td>
</tr>
<tr>
<td>Last 32</td>
<td>75139</td>
<td>0.86</td>
</tr>
</tbody>
</table>

*The unit for currency is U.S. dollar

4.1 Stage 1: Decision of Accepting an Order or Not

Given a generated order popped up to a specific driver, a driver makes decision on whether to use TNC app to accept orders or to decline it and take alternatives such as using natural passenger sources to receive orders, e.g. phone call, airport pickup, hotel pickup, passengers on the roadside. We assume a driver $i$ at time $t$ will receive utility of $u_{at}^{\text{app}}$ if he/she accepts order from TNC app, and $u_{at}^{\text{not}}$ if not. Individual subscripts are suppressed given homogenous assumption for taxi drivers who are all employed by taxi operators.

Two possible outcomes will occur after the drivers accept offers from the app. If a driver is committed to the order, the transaction will be fulfilled and the driver will gain utility including fare, tips, subsidy, and sales promotion netting the cost. In contrast, if a driver takes an order as unprofitable or risky, he/she still have chance to cancel the current order to prevent further cost. By using an indication function, we form the utility of accepting an order as following:

$$u_{at} = D_{at} u_{at}^{\text{app}} + (1 - D_{at}) u_{at}^{\text{not}} + e_{at},$$  

where $D_u$ is a dummy variable indicating whether transaction is fulfilled, $u_{sl}$ is the utility if order is fulfilled, and $u_{st}$ is that if order is cancelled. We specify $\varepsilon_{alt}$ to capture unobserved information by econometricians such as location information, which follows type I extreme distribution.

Other than unobserved information, there are three components that account for drivers’ utility when transactions are fulfilled as can be seen in equation (2). Drivers gain utility from the attribute of using app to accept an order and all forms of bonus net the cost if online-pay is used for that order. Attribute $A_u$ here refers to an aggregation of tangible and intangible product attributes which lies in a multidimensional space (Erdem et al 2008). It includes product specific characteristics that would generate utility to users when they choose to use app to accept orders. The second component includes the three formats of bonus for taxi drivers. First one is cash back bonus $B_t^{cb}$ if passengers use online-pay, which is used for the purpose of promoting using app and online-pay function, redeemed from TNC platform and its financial partners. Second one is passenger tip $B_t^{tip}$, which is revealed before drivers make decision, to increase drivers’ willingness to accept specific orders. Third one is platform subsidy $B_t^{sub}$, which is similar to passenger tip as used to encourage drivers to accept orders but provided by the TNC platform. Despite these monetary rewards, using online-pay may incur cost due to potential transaction cost as well as loss of instant gratification. We use additive form with scalars for attribute, monetary unit of bonus and online-pay associated cost as following:

$$u_{sl} = \beta_{a1}A_u + \beta_{a2} \left( D_{pt} \times B_t^{cb} + B_t^{tip} + B_t^{sub} \right) + D_{pt}c_{alt} ,$$

where $\beta_{a1}$ represents weight of utility from attributes of app. We specify a constant weight $\beta_{a2}$ to monetary rewards in different forms since they are the same in units as well as formats. $D_{pt}$ is a dummy variable indicating whether passengers use online-pay, and $c_{alt}$ is online-pay associated cost.

When a transaction is cancelled, drivers still receive attribute value $A_u$ associated with using the app to accept orders since the usage associated with accepting an order has already happened. In addition, they receive utility associated with cancelling orders $c_{a2}$, since cancellation prevents further cost of a risky order. We formulate utility of cancelling an order as following:

$$u_{st} = \beta_{a1}A_u + c_{a2} .$$

Taking both cases together, we have utility of accepting an order as the following expression:

$$u_{sl} = \beta_{a1}A_u + D_{pt} \left( \beta_{a2} \left( D_{pt} B_t^{cb} + B_t^{tip} + B_t^{sub} \right) - D_{pt}c_{alt} \right) + \left( 1 - D_u \right) c_{a2} + \varepsilon_{alt} .$$

Taxi drivers would make decision of not to accept an order when they receive higher utility level from outside goods. We model the utility of outside goods $u_{s0t}$ to be summation of constant level $c_{a0}$ plus a stochastic error term that captures unobserved utilities.
Given that the TNC platform is newly introduced to the market, drivers are not fully certain about the latent utility from the very beginning. Therefore, before drivers make decision on whether to use app to receive orders, they firstly form expectation of the utility from two alternatives based on information updated to period $t$, and choose the alternative that maximizes their expected utility. The major source of information drivers would use to improve their perception of utility is usage experience, since it provides precise information that dominates other channels. We define information set $I_t$ as the cumulative usage experience. By taking expectation conditional on $I_t$, and rearranging our expected utility function by linearity of conditional expectation, we have the following expressions for conditional expectation of latent utility for different alternatives:

$$
E(u_{at0} | I_t) = \beta_{a1} E(A_a | I_t) + \Pr(D_{at} | I_t) \left( \beta_{a2} \left( \Pr(D_{at} | D_{at}, I_t) B_{a1}^{up} + B_{a1}^{up} + B_{a1}^{upb} \right) - \Pr(D_{at} | D_{at}, I_t) c_{a1} \right) \\
+ \left(1 - \Pr(D_{at} | I_t) \right) c_{a2} + \epsilon_{a0t},
$$

(6)

$$
E(u_{at0} | I_t) = c_{a0} + \epsilon_{a0t}.
$$

(7)

By modeling this way, we let uncertainty be absorbed into the three components: expected value of attribute $E(A_a | I_t)$, the probability of fulfilling an order $\Pr(D_{at} | I_t)$ and the probability that a passenger will pay online $\Pr(D_{at} | D_{at}, I_t)$. We assume drivers behave as Bayesian learners who update their expectations based on $I_t$. Specifically, since drivers might get involved into three sequential decisions and receive usage experience from each of them, we let drivers update specific decisions based on usage experience of corresponding decision before time $t$. Therefore, $\Pr(D_{at} | I_t)$ and $\Pr(D_{at} | D_{at}, I_t)$ would be updated with stage 2 decision and stage 3 decision respectively, which will be explained in later session. $E(A_a | I_t)$ is updated with stage 1 decision that drivers experience from the very beginning to time $t$.

We now explicitly explain how $E(A_a | I_t)$ is formed with Bayesian learning process. Before starting to use app to accept orders, drivers would have prior information about true attribute of accepting orders from the app. We model the prior information following $N(A_{a0}, \sigma_{a0}^2)$ to accommodate a potentially biased prior belief $A_{a0}$ and drivers’ uncertainty $\sigma_{a0}^2$. Drivers make first-time decision based on prior information only, such that first time attribute $A_a$ is drawn from prior distribution $N(A_{a0}, \sigma_{a0}^2)$. Define $\sigma_{a0}^2$ as the variance of driver $i$’s perception of mean attribute level at the very beginning, we have

$$
E(A_a | I_0) = A_{a0}, \text{ and } \sigma_{A_{a0}}^2 = Var(A_a | I_0) = E\left(\left( A_a - A_{a0} \right)^2 | I_0 \right) = \sigma_{a0}^2.
$$

(8)
Drivers update their belief in attribute value and uncertainty when they are better informed with signals. Such signals are drivers’ own usage experience in which they can perceive the true attribute value of using app to accept orders with some noises. The noises can be derived from the variability of true attribute value itself or variability associated with specific context in usage experience. To make the Bayesian update conjugate, we assume that signal of app’s true attribute value, denoted as $A_t^e$, follows normal distribution according to

$$A_t^e \sim N(A_{at}, \sigma_{at}^2).$$

(9)

$A_{at}$ is the mean of signal which equals to true attribute value, and $\sigma_{at}^2$ captures variance of signal.

We model drivers update when they receive one more usage experience, and stick with the initial perception if not. Specifically, when a driver experiences using app to take an order at time $t-1$, he/she updates perception as a weighted average of perception formed in last time period $E\left(A_u \mid I_{t-1}\right)$ and the newly received signal $A_{t-1}^e$. To be consistent with the intuition that more precise signal would lead drivers’ perception to be closer to true attribute value, we model the weights as precision parameters as inverse of perception variance and that of signal according to

$$E\left(A_u \mid I_t\right) = D_{at} \times \frac{E\left(A_u \mid I_{t-1}\right)}{\sigma_{at}^2} + \frac{(1 - D_{at}) \times E\left(A_u \mid I_{t-1}\right)}{\sigma_{at}^2} \times \frac{1}{\sigma_{at}^2},$$

(10)

$$\sigma_{At}^2 = D_{at} \times \frac{1}{\sigma_{at}^2} + \frac{(1 - D_{at}) \times \sigma_{at}^2}{\sigma_{at}^2},$$

(11)

where $D_{at}$ is a dummy variable indicating whether drivers accept an app order. Posterior uncertainty is updated as the inverse of sum of inverse of prior uncertainty and inverse of signal variance if signal is received, which allows diminishing uncertainty with gain of usage experience and faster uncertainty diminishing with less noisy signals.

Rational drivers would form beliefs of $Pr\left(D_{at} \mid I_t\right)$ and $Pr\left(D_{pt} \mid D_{at}, I_t\right)$ following rules in stage 2 and stage 3 conditional on corresponding usage experience till time $t$. Assume that $Pr\left(D_{at} \mid I_t\right)$ and $Pr\left(D_{pt} \mid D_{at}, I_t\right)$ are formed and that the error terms $\varepsilon_{at0}$ and $\varepsilon_{at1}$ are independently and identically distributed with type-I extreme distribution, we obtain the probability that a driver would accept an order from TNC app channel conditional on information $I_t$ and the stage specific log likelihood function as follows:
Optimizing Two Sided Promotion for Transportation Network Companies

\[
\Pr(D_{at} | I_t) = \frac{\exp(U_{at})}{\exp(U_{at}) + \exp(c_{at})},
\]

where

\[
U_{at} = \beta_{a1} E(A_t | I_t) + \Pr(D_{at} | I_t) \left( \beta_{a2} \left( \Pr(D_{pt} | D_{at}, I_t) B_t^{th} + B_t^{tip} + B_t^{tub} \right) - \Pr(D_{pt} | D_{at}, I_t) c_{at} \right)
+ \left( 1 - \Pr(D_{at} | I_t) \right) c_{at2},
\]

\[
L(\beta_1, \beta_2, \beta_3) = \sum_{i=1}^{n} \sum_{t=1}^{T} \log \Pr(D_{at} | I_t) D_{at} + \log \left( 1 - \Pr(D_{at} | I_t) \right) \left( 1 - D_{at} \right).
\]

4.2 Stage 2: Decision of Cancelling an Order or Fulfilling

Once drivers have accepted an order from the TNC platform they still have chance to cancel it if they obtain more information signaling low quality of the order, or if better alternative goods appear. We assume a driver \(i\) at time \(t\) will receive utility of \(u_{str}\) if he/she fulfills an order from TNC app, and \(u_{sot}\) if not.

There are six systematic components constituting drivers’ utilities when they decide on fulfilling or not. Specifically it includes cash back bonus \(B_t^{th}\) if a passenger uses online-pay, passenger tip \(B_t^{tip}\), platform driver subsidy \(B_t^{tub}\), cost associated with online-pay \(c_{s1}\), as well as initially uncertain attribute value of the cancelling feature \(A_t\) in utility if a driver is about to fulfill an order. Utility for outside goods is modelled as a constant \(c_{s0}\). We introduce error terms \(\epsilon_{str}\) and \(\epsilon_{sot}\) respectively for fulfilling an order and cancelling an order to represent additional unobserved information. We specify latent utility of fulfilling an order or cancelling that order as a linear additive form by the following way:

\[
u_{str} = \beta_{a1} A_t + \beta_{a2} B_t^{tub} + \beta_{a3} B_t^{tip} + D_{pt} \left( \beta_{a4} B_t^{th} + c_{s1} \right) + \epsilon_{str},
\]

\[
u_{sot} = c_{s0} + \epsilon_{sot}.
\]

\(D_{pt}\) is an indicating function governing utility associated with using online-pay. Only when online-pay is used, drivers would gain cash back from the platform while incurring transaction cost. \(\beta_{a1}\) is the weight for attribute value, \(\beta_{a2}\) captures the weight for platform subsidy. \(\beta_{a3}\) measures the weight for revealed tip from passenger. And \(\beta_{a4}\) represents the weight for online-pay contingent cash back. The reason of giving different weights to different formats of monetary rewards here is that we suspect that revealed tips as well as subsidy might play an additional role as signaling quality of orders. We conjecture that a high tip from passenger might convey extra information from passenger, for example, indicating potentially associated extra cost. Similarly order specific subsidy from platform might also convey information known by the platform, whereas such effect does not exist for the cash back bonus. Those rewards specific extra information indicates sensitivity parameters as compound of sensitivity to monetary rewards and that to extra information. The sign of parameters would be dominated by the stronger effect. This is not modeled in
stage 1 by the same way since same information is already captured by \( \Pr(D_{st} \mid I_t) \), which avoids overlapped information and helps to identify cancelling cost\( c_{st} \).

Recall that cancelling function is newly introduced, taxi drivers are not certain about how the function works, such that they might overact or underact to cancel orders. To rationalize our model, we assume that drivers will form expectation of latent utility conditional on information set up to time \( t \) to make decision of cancelling order or not. Given that monetary rewards are revealed precisely before decision making, all the uncertainty in latent utility would stem from \( A_t \) as an aggregation of characteristics of the cancelling feature that is most likely to be uncertain for taxi drivers, as well as \( D_{st} \) which captures uncertain level associated with next stage decision. Accordingly, the expected utility conditional on information set \( I_t \) is given by

\[
E(u_{st} \mid I_t) = \beta_{st}E(A_t \mid I_t) + \beta_{st}B_{st}^{sb} + \beta_{st}B_{st}^{qp} + \Pr(D_{pt} \mid D_{st}, I_t)(\beta_{st}B_{st}^{ch} + c_{st}) + \epsilon_{st},
\]

(17)

\[
E(u_{sst} \mid I_t) = c_{st} + \epsilon_{sst}.
\]

(18)

Drivers need to form belief of attribute of fulfilling through their experience. Similar to the model of perceived attribute value of accepting orders from the app, we model these learning processes following Bayesian updating rule with prior perceived value following \( N(A_{st}, \sigma_{st}^2) \), and signal following \( N(A_{st}, \sigma_{st}^2) \). We suppress the updating rules here for a concise interpretation and let \( E(A_t \mid I_t) \) represent Bayesian-updated drivers’ belief of perceived attribute value for fulfilling an order at time \( t \). In addition, drivers would form beliefs about passengers’ willingness to use online-pay as \( \Pr(D_{pt} \mid D_{st}, I_t) \) conditional on usage experience till time \( t \) by following the rule addressed in stage 3. We simply model the error term following type-I extreme value distribution, which result in a closed-form logit formula for probability of fulfilling an order conditional on the information set. We present the probability of fulfilling an order as well as stage 2 log likelihood function as following:

\[
\Pr(D_{st} \mid I_t) = \frac{\exp(\beta_{st}E(A_t \mid I_t) + \beta_{st}B_{st}^{sb} + \beta_{st}B_{st}^{qp} + \Pr(D_{pt} \mid D_{st}, I_t)(\beta_{st}B_{st}^{ch} + c_{st}))}{\exp(\beta_{st}E(A_t \mid I_t) + \beta_{st}B_{st}^{sb} + \beta_{st}B_{st}^{qp} + \Pr(D_{pt} \mid D_{st}, I_t)(\beta_{st}B_{st}^{ch} + c_{st}))+\exp(\epsilon_{st})},
\]

(19)

\[
L_2(\beta, \beta_p) = \sum_{i=1}^{n} \sum_{t=1}^{T} \log \Pr_t(D_{st} \mid I_t)D_{st} + \log(1 - \Pr_t(D_{st} \mid I_t))(1 - D_{st}).
\]

(20)

### 4.3 Stage 3: Decision of Online Pay and Redeem Sales Promotion by Passengers

Conditional on an order fulfilled, passengers would make decision on whether to use online-pay for taxi fare. Given that online-pay function is newly introduced to passengers, we conjecture whole population of passengers as a Bayesian learner with perceived attribute associated with online-pay function converged to
a stationary level from a biased starting point conditional on cash back policy. In addition, the launching time of online-pay is later than the starting point of each driver’s usage experience, implying that drivers would experience the trend simultaneously.

Given that online-pay would potentially lead to cash back bonus from the platform, drivers would calculate their expected utility in stage 1 and stage 2 with their expectations of receiving an online-paid order. We assume that drivers would form their beliefs of receiving an online-paid order by their own experience interacted with their passengers. Note that passenger(s) in drivers interaction set is not one specific passenger, but many passengers who interact with a specific driver very sparsely. This description indicates that drivers’ learning is not about one specific passenger but a sample inferring the general trend of how the passenger population evolves with respect to using online-pay.

A rational driver knows that passengers’ information set is limited to passenger side sales promotion $C^{cb}_t$, tips they promised when initiate the order $B^{tip}_t$, attribute value of using online-pay function $A_p$ and the utility from outside alternative payment methods $c_{p0}$ such as cash or transportation card. Those components except the utility of outside goods constitute systematic part of drivers’ latent utility function of passenger using online-pay. It follows a linear additive form with $\beta_{p1}, \beta_{p2}$ and $\beta_{p3}$ as corresponding weights. To capture unobserved information, type-I extreme distributed error terms are included. Accordingly, utility functions of taking online-pay and alternative way are given by:

$$u_{p1t} = \beta_{p1}A_p + \beta_{p2}C^{cb}_t + \beta_{p3}B^{tip}_t + e_{p1t},$$  \hspace{1cm} (21)

$$u_{p0t} = c_{p0} + e_{p0t}.$$  \hspace{1cm} (22)

Drivers form expectation over passengers’ willingness to use online-pay by cumulative usage experience. As drivers are certain about sales promotion policy for passengers and revealed tip amount, usage experience are mostly used to signal the perceived aggregate attribute of using online-pay which is newly introduced. Accordingly, we form an expected utility from drivers’ perspective and corresponding drivers’ belief in the probability of receiving a potentially online-paid order conditional on time information set $I_t$ for an fulfilled order as following:

$$E(u_{p1t} | D_{st}, I_t) = \beta_{p1}E(A_p | I_t) + \beta_{p2}C^{cb}_t + \beta_{p3}B^{tip}_t + e_{p1t},$$  \hspace{1cm} (23)

$$E(u_{p0t} | D_{st}, I_t) = c_{p0} + e_{p0t},$$  \hspace{1cm} (24)

$$\Pr(D_{st} | D_{st}, I_t) = \frac{\exp\left(\beta_{p1}E(A_p | I_t) + \beta_{p2}C^{cb}_t + \beta_{p3}B^{tip}_t\right)}{\exp\left(\beta_{p1}E(A_p | I_t) + \beta_{p2}C^{cb}_t + \beta_{p3}B^{tip}_t\right) + \exp(c_{p0})}.$$  \hspace{1cm} (25)
Drivers would update about their belief of attribute based on their usage experience. We model drivers’ prior belief of attribute following $N\left(A_{p,t}, \sigma_{pt}^2\right)$ and received signal about attribute following $N\left(A_{p,t}, \sigma_{pt}^2\right)$. Every time when a driver fulfills an order and the corresponding passenger(s) uses online-pay for fare, driver’s perception over attribute would be updated following Bayesian rule similarly as we described for stage 1. Passengers would gain cash back if they use online-pay feature, we conjecture that cash back for passengers would foster incentive for using online-pay. Revealed tips, on the other hand, incur cost for passengers for either pay online or offline.

Following literature of structural model by Rust (1987), Hotz and Miller (1993), and Bajari et al. (2007), we assume drivers would be able to form a consistent belief of the population level trend of using online-pay with updating from their usage experience. From perspective of structural model, state transition as passengers’ decision of using online-pay would be consistently inferred by drivers through usage experience. This assumption allows us to link realized decisions of passengers with perceived probability of drivers to identify associated parameters as following:

$$L_3(\beta_p) = \sum_{i=1}^{m} \sum_{t=1}^{T} \log \Pr(D_{pt} | D_{st}, I_t)D_{pt} + \log \left(1 - \Pr(D_{pt} | D_{st}, I_t)\right)(1 - D_{pt})\ .$$

Since the transition rule is for general trend at the population level, the assumption means that the general trend evolves following perceived function conditional on fulfilled orders. In other words, all else being equal, the general trend of using online-pay will slow down were all drivers fulfill orders infrequently. Whereas the general trend conditional on fulfilled orders will be constant.

5. Estimation Result

5.1 Identification

We briefly talk about the identification of our model in two steps. In first step, we explain the identification of one typical Bayesian learning process following Crawford and Shum (2005). In second step, we explain the identification of our full model.

There are three sets of parameters in a typical Bayesian learning model for discrete choice with only one uncertain attribute value. The first and most intuitive one is the coefficients associated with exogenous variables such as coefficients for different forms of sales promotion in our study. Those coefficients are identified by the variation of variables associated with them. The second set of variables includes true attribute value, prior attribute value and constant terms in each Bayesian updating process, among which only two can be identified since only difference matters in discrete choice model. And our learning pattern allows identification of the difference between prior and true value from the difference of decisions between earlier stages and later ones. In other words, the variation of different decisions and the variation along the time allow us to identify two parameters. Since we are more interested in difference
between true and prior attribute value, and we want to test whether the true attribute value is higher or lower than the prior attribute value, we normalize true attribute value at zero and leave prior attribute value and constant with freedom. This is also the most computationally effective way for minimization algorithm. The third set of parameters are prior variance and true variance of attributes for each of the Bayesian learning, such as $\sigma^2_{a0}$ and $\sigma^2_{a1}$, $\sigma^2_{s0}$ and $\sigma^2_{s1}$, and $\sigma^2_{p0}$ and $\sigma^2_{p1}$ correspondingly. We are only allowed to identify one of prior variance and true variance in each Bayesian updating because only relative difference between those two variances matters. Given a fixed prior mean value as the starting point and a fixed true mean value as the converged endpoint, the latent utility still has freedom in the speed of convergence along with time dimension. This convergence rate can be visualized as a curvature along with the time series, and identifies relative variance between prior variance and posterior. In our model, we normalize true value variances as 10, and identify the prior variance to investigate the uncertainty level of attributes before any usage experience.

The identification for the full model is straightforward given our above discussion about identification for Bayesian learning. Given observations of three sequential decisions as drivers’ decisions of accepting orders, drivers’ decisions of fulfilling orders and passengers’ decisions of paying online in drivers’ perception, we can identify Bayesian updating associated parameters as $A_{a0}$, $\sigma^2_{a1}$, $A_{s0}$, $\sigma^2_{s1}$, $A_{p0}$ and $\sigma^2_{p1}$ from the difference of latent perceived attribute between earlier time point and later time points, and the curvature of perceived attribute for each of the decisions. Other parameters are components in generalized linear formula, which follows typical identification rule of discrete choice model. Given three sequential decision choices data, we are allowed to identify linear components by the difference of latent utility between different choices when type-I extreme error is used, which imposes fixed variability of error term. One concern would be the identification of parameters associated with probability of online-pay and probability of cancelling in stage 1 decision since they are functions of sales promotion, and some sales promotion variables are overlapped in different decisions. It can be erased by the Bayesian learning in later stages since the mechanism of Bayesian learning itself introduces additional information from past experience of decisions of online pay and decisions of fulfilling. With those exclusive variables and logit transformation which imposes a non-linear transformation of variables, our model avoids identification difficulty.

5.2 Estimation Specification and Model Fit

We use simulated MLE method to recover parameters by following two-stage estimation method. With independent errors across the stages, the log likelihood function could be divided into three pieces.

$$L(\beta_a, \beta_s, \beta_p) = L_3(\beta_p) + L_2(\beta_s, \beta_p) + L_1(\beta_a, \beta_s, \beta_p)$$ (27)
$L_3(\beta_p)$ - the log likelihood contribution of paying online (redeem cash back);

$L_2(\beta_s, \beta_p)$ - the log likelihood contribution of fulfilling an order;

$L_1(\beta_a, \beta_s, \beta_p)$ - the log likelihood contribution of accepting an order;

\[
\beta_p = \{ A_{p0}, \log(\sigma_{p1}^2), \log(\beta_{p1}), \beta_{p2}, \beta_{p3}, c_{p0} \}
\]

\[
\beta_s = \{ A_{s0}, \log(\sigma_{s1}^2), \log(\beta_{s1}), \beta_{s2}, \beta_{s3}, \beta_{s4}, c_{s1}, c_{s0} \}
\]

\[
\beta_a = \{ A_{a0}, \log(\sigma_{a1}^2), \log(\beta_{a1}), \beta_{a2}, c_{a2}, c_{a1}, c_{a0} \}
\]

Here $\beta_p$ are state parameters, and $\beta_s, \beta_a$ are utility parameters. Consistent estimates of $\beta_p$ can be identified from maximizing $L_3(\beta_p)$. With the estimates of $\beta_p$, consistent estimates of $\beta_s$ can be found by optimizing $L_2(\beta_s, \beta_p)$. And finally, coupled by estimates of $\beta_s, \beta_p$, estimates of $\beta_a$ can be obtained by maximizing $L_1(\beta_a, \beta_s, \beta_p)$.

The maximization of parameters in stage 3 now reduces to a typical Bayesian learning model. More specifically, we use typical maximal simulated likelihood method proposed by Erdem and Keane (1996) to recover state transition parameters in stage 3, with the attribute perception simulated and variance integrated numerically. Recall that state transition is decision specific, and in our case if order is cancelled, there would be no online-pay and corresponding learning, we only need data whose stage 2 decision is not canceling to estimate the conditional belief.

More challenges come in recovering utility parameters in stage 1 and stage 2 in which we have multiple learnings. When forming likelihood, we need to not only update learning for current stage decision, but also form belief of probability of outcome in later stages which are updated following Bayesian learning rule conditional on former stage outcome. On the contrary, decision of taking outside goods in current stage not only prohibits learning for current stage attribute, but also limits that for next stage. Compared with traditional Bayesian learning model with only one attribute-learning, our model incurs more sophisticated framework since it needs to accommodate multiple learning. Compared with structural models with steady policy function, our policy function is not stationary but updating with a Bayesian learning process conditional on former decision in sequence. This sequential and conditional decision process naturally renders to a forward-simulation based method as drawing decisions sequentially to form likelihood. Given outcome variables for last transaction, we update perceived attribute values for all of the three learning process for each individual and update policy function for next period based on updated perceived attribute values. Given updated policy function and observed outcome
for current stage, we simulate outcome decisions of later stages for next time period. We keep this loop through each time period. Similar with Erdem and Keane (1996), we numerically integrate over perceived uncertainty by simulating many times for each individual, and form a numerically integrated likelihood function.

Figure 2. Fitness by Comparing Nonparametric Aggregate Estimation Vs. Prediction from Our Model

Our model shows good performance of fitness with data. Since our dependent variable is discrete choice variable, we use McFadden’s pseudo $R^2$ (McFadden 1974) as a reference of model fit. The numerical results in Table 3 show that pseudo $R^2$s of the three stages are all above 0.2, which is interpreted as excellent fit according to McFadden’s discussion in behavioral travel modelling (Hensher and Stopher 1979). To visualize the goodness of fit we plot the average probability of decisions over different individuals for a specific cumulative number of transactions in Figure 2, where red dot indicates nonparametric average from our data and black one represents predictive value from our parametric model. The y-axis in Figure 2’s charts respectively represents the probability drivers will accept an order, the probability that transaction is not cancelled conditional on drivers’ acceptance, and the probability that passengers will pay online conditional on a fulfilled order. Nonparametric results in our charts show
general ascending and concave patterns for all of those probabilities, which indicate individuals undervalue TNC app associated features at the very beginning but gradually learn and use them more frequently with accumulation of usage experience. By checking the fitness of black dots, we find that our model recovers learning pattern by a smoother concave and increasing function, which in general fits very well except two tails where data are too sparse.

5.3 Estimation Results

In this session, we present the estimation results and insights associated with the numbers. We present the results ordered consistently with our model, started from decisions of drivers and followed with state transition as drivers’ belief in passengers’ decision of using online-pay. All of the point estimation as well as standard error are presented in Table 3. In addition, we shows the latent learning process by explicitly display the updated perceived attributes and updated perceived variance of the three decisions to help understanding the learning process. The attributes are simulated based on estimated parameters, which are shown in Figure 3.

5.3.1 Stage 1

As can be seen in the top panel of Table 3, we estimate the parameter of sensitivity to monetary rewards to be 14.3350, which implies the effectiveness of expected sales promotion in drivers’ willingness to accept order from TNC channel. As the expected cash back is over drivers’ belief in passengers’ willingness to redeem cash back and that in the probability of cancelling the order in the next stage, this description implies that drivers would be more willing to accept an order when he/she believes that passengers would be highly probable to redeem sales promotion, the probability that he/she would cancel the order in the next stage is low, and big amount of sales promotion is promised.

Our model allows us to recover latent utility parameters associated with online-pay function, cancelling function and opportunity cost for taking outside goods. Specifically, utility for cancelling an order $c_{a2}$ is estimated to be 12.0888, which is equivalent to 0.85 USD once we adjust it with monetary coefficient. This measure indicates that allowing strategic cancelling would lead drivers to better off conditions since drivers can eliminate orders which signal uncertainty and risk of further cost. Cost of using online pay $c_{o1}$ is estimated to be -15.2681, or 1.07 USD. Such cost might result from transaction cost of using online-pay as well as the discounted utility by delayed gratification from work. Opportunity cost for outside goods $c_{a0}$ is -8.3884, implying that outside goods in general generate inferior attribute value when we have no online-pay options, not allowing any cancellation feature and no monetary rewards to drivers. However, coupled with cost of using online-pay, utility of cancelled order and associated probabilities, outside goods might show superiority. This is consistent with intuition that usage complexity needs to be compensated. Considering the effectiveness of monetary rewards as well as utility incurred from online-pay and cancelling in the scenario when uncertainty is eliminated, simple calculation from our results shows
that compensation as low as 0.65 USD would be enough to cover cost incurred by using the app, which justifies the necessity of subsidy for current TNC companies.

Table 3. Estimation Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E</th>
</tr>
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<tbody>
<tr>
<td>Decision of Accepting Order</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A_{a0}$</td>
<td>-4.6644***</td>
<td>1.6006</td>
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<td>$A_{a1}$</td>
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<td>$\sigma^2_{a0}$</td>
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<td>log($\sigma^2_{a1}$)</td>
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<td>5.9296</td>
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<td>log($\beta_{a1}$) (attribute)</td>
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<td>$\beta_{a2}$ (monetary scalar)</td>
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<td>3.2362</td>
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<tr>
<td>$c_{a2}$ (cancelling cost)</td>
<td>12.0888***</td>
<td>1.1631</td>
</tr>
<tr>
<td>$c_{a1}$ (online-pay cost)</td>
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</tr>
<tr>
<td>$c_{a0}$</td>
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<td>$\beta_{s4}$ (driver cashback)</td>
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</tr>
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<td>0.0247</td>
</tr>
</tbody>
</table>

Pseudo R-sq

| Decision of Accepting Order | 0.5435     |
| Decision of Fulfilling an Order | 0.3613     |
| Decision of Online-pay | 0.2499     |

Note: *** and ** denote significance at 1% and 5%, respectively.

We also find strong evidence of learning process. The prior parameter for app attribute $A_{a0}$ is -4.6644, which is significantly lower than 0-normalized posterior parameter $A_{a1}$ . This difference indicates
undervaluation of TNC app by drivers before they start to use it, and suggests learning would help to eliminate the perception bias gradually. We estimate $\log(\sigma_{a1}^2)$ to be 1.7622, which suggests variance of signal $\sigma_{a1}^2$ of 5.8252, smaller than 10-normalized experience variability parameter. This indicates that signal is much clearer than the prior belief. Thus drivers’ learning process about the attribute of using app to accept order is comparably fast. The smaller the variability parameter, the more the weight for signal from usage experience, and the faster the learning process is. Note that our estimation results in stage 3 and stage 2 show that learning processes for using online-pay and cancelling order are comparably slow, our results explain why TNC platform in our example uses sales promotion associated with online-pay function, rather than associated with per-use.

Figure 3. Attribute Values and Uncertainties of Learning Processes

5.3.2 Stage 2
The positive and significant coefficient on sales promotion for drivers from cash back indicates the effectiveness of sales promotion in reducing drivers’ tendency to cancel a generated order. Specifically, as
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cash back from platform is an expectation over drivers’ belief of the probability of receiving cash back (same as probability of using online-pay), a positive coefficient suggests that the higher perceived probability of receiving cash back, the less drivers are willing to cancel an order. Coupled with the claim in stage 3 that belief in probability of receiving cash back is a function of platform sales promotion strategy for passengers, it is insightful to address that sales promotion strategy on passenger side also have indirect and positive effect on drivers’ willingness to continue an accepted order. On the other hand, we estimate coefficients on passengers’ tips to be slightly negative (-0.0990). This supports our conjecture of a double-sided role of passengers’ tips. On one hand, it results in higher utility level by providing direct monetary incentives; on the other hand, it signals bad quality of a specific order such that passengers have to increase the amount of tips to increase the probability that their order could be taken, which increases drivers’ willingness to cancel. In our example, the second role of revealed tips dominates its effect. In contrast, the positive sign of coefficient on platform subsidy implies that subsidy either signals very limited information of bad quality or doesn’t signal at all, leaving the monetary incentive dominating the overall impact in utility function. This is consistent with our expectation since the subsidy at the early stage is not dynamic but constant for several short-term periods for all drivers, thus conveying very limited order specific information.

The attribute prior parameter $A_{0}$ is estimated to be -1.3794 with posterior parameter $A_{1}$ normalized to 0, implying that drivers undervalue the perceived utility under uncertainty, and thus overact to cancel existed orders. The experience variability parameter $\log(\sigma_{s1}^{2})$ is estimated to be 4.9423. Compared with 10-normalized initial quality variance, it is much larger in scale, which implies a slow learning process. Similar to our argument about direct versus indirect effects of sales promotion, this learning pattern confirms our previous conjecture that platform has to lasts the sales promotion for a certain length of period to ensure adequate learning.

We also identify two cost parameters associated with stage 2. Given that true attribute value is normalized to 0, opportunity cost parameter $c_{0}$ is estimated to be -1.3392, indicating inferior utility of cancelled order. Cost associated with using online-pay is -10.1917, which is consistent with our finding in stage 1.

5.3.3 Stage 3

From drivers’ perspective, passengers would incline to use online-pay when the amount of cash back from platform, as a bonus for using online-pay, is high, implying the effectiveness of sales promotion on passenger side ($\beta_{p2}$ is estimated to be 0.2379). In addition, the higher the tips set by passengers, the lower the willingness to pay online (-1.2047 coefficient estimate), a claim consistent with the intuition that
passengers who are generous on giving tips are less sensitive to monetary sales promotion and less likely to redeem cash back bonus by switching to an unfamiliar payment method.

With regard to the learning, given that we fix the true attribute $A_{p1}$ at 0, the estimated negative prior attribute $A_{p0}$ indicates undervaluation of using online-pay before drivers start to use and be informed about the quality of app. In addition, to compare with the prior uncertainty of attribute $\sigma_{p0}^2$ fixed at 10, we estimate $\log(\sigma_{p1}^2)$ to be 3.2971, equivalent to say $\sigma_{p1}^2$ is much higher than $\sigma_{p0}^2$, indicating a slow learning speed of passenger population since weights for learning updates is inverse of the uncertainty level. The utility for outside goods are estimated to be -1.3423 with attribute of online-pay being normalized at 0. Thus online-pay function in general generates positive utility compared with traditional cash transaction.

Recall our findings about sales promotion coefficients with a dynamic perspective, they suggest effectiveness of sales promotion in the learning process since direct effect of sales promotion encourages static willingness to use, which further helps accumulating usage experience and fosters users’ learning, resulting in indirect effect in willingness to use in the next time period as the negative perception bias diminishes. Coupled with further implication that a faster learning should be accommodated with a shorter sales promotion, whereas slower one with a longer sales promotion, our finding of the slow learning process for using online-pay explains the observation that TNC platform launches sales promotion associated with online-pay function for a long period during the introduction of the app.

Our estimation results still have limitation in interpretation. As sales promotion plays significant role in each of decision stages, and learning in each stage of decisions have impact on drivers’ willingness to use through linked but non-linear model, our results failed to display the overall direct effect of sales promotion and indirect effect imbedded in multiple learnings. In addition, effect of promotion strategy on passenger side is not shown explicitly. As we show in stage 2 and stage 3, sales promotion on passenger side would make impacts on drivers’ perception of passengers’ decision, which would in turn affect drivers’ decisions. This impact is difficult to disentangle and interpret given the non-linear function we impose in the structural model. To provide a more practical and heuristic answer for optimizing sales promotion for TNC platform and construct a more straightforward link between sales promotion policies and corresponding outcomes, we use simulation based method to recover several outcomes given different versions of counterfactual sales promotion policies as described in the following section, including a comparison between long term policy versus short one, as well as different designs of strategies on passenger side and driver side.

6. Policy Simulation

We conduct three sets of policy simulation here to understand the impact of two-sided promotion on outcome variables. Specifically, we set our outcome variable as fulfillment rate, which is equivalent to joint probability that an order is accepted and not cancelled, and online-pay rate as the final outcome in
our sequence because they are key measurements of TNC platform performance. In the first set of policy simulation, we focus on the time dimension, in which we try to differentiate the learning related indirect effect from sales promotion induced direct effect on the platform performance. The second set simulation focuses on effects of promotions on two sides. Our estimation result in the previous section shows qualitative result of how two sides of sales promotion impact drivers’ willingness to use app, but doesn’t answer the valence of sales promotion from each side because of the indirect link through different stages with nonlinear function. Therefore, our second set of policy simulation compares the effectiveness of sales promotion effects on two sides, and generates implication about how to balance sales promotion between two sides with the objective of maximizing the overall platform operation performance. Given the finding from our model estimation and first two sets of policy simulation, in the third set of policy simulation, we modify different cash back policies by following heuristic rules, with a goal to find a policy that increase the online-pay rate while be more cost effective for the platform.

We use our estimation results to simulate a driver’s decision of accepting an order, whether a transaction is fulfilled, and whether a driver receives cash back bonus. Specifically based on our structural model, in each loop of simulation, we firstly use updated belief of the probability that a passenger will use online-pay conditional on the transaction is fulfilled and that driver will fulfill the order conditional on he/she will accept the order to simulate a driver’s decision of accepting an order. Then we simulate whether the transaction is indeed fulfilled and whether the transaction is ended with online-pay. Then we update perceived value of three kinds of attributes by using Bayesian learning, and use the updated belief in the next time period. We simulate each policy for 100 times, and take the average as our result.

6.1 Estimating Indirect Effect of Sales Promotion

Indirect effect of sales promotion is implicitly shown by the existence of drivers’ learning in our model. 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 has for drivers’ decisions. We firstly simulate a baseline of drivers’ decisions across time period. By identifying a benchmark point in time horizon that perceived value is stationary around true value from that on, which indicates that learning is no longer updated, we then visualize direct effect by simulating a case of 0.15 USD (equivalent to 1 RMB) cash back reduction in sales promotion policy from the benchmark point. Lastly, we simulate the third case with penalty before benchmark point such that usage experience as well as learning is prohibited, then we set promotion to be again 0.15 USD less from the benchmark point. Since the sales promotion is identical from benchmark point such that direct effect is the same, we visualize the indirect effect by presenting the difference between the second and third simulation, which is explained by the learning effect before the benchmark point only.
We aggregate the fulfillment rate and online-pay rate with respect to cumulative transaction number and show our results in Figure 4. In the baseline case (black line), due to the fact that sales promotion exists from a certain point till the end, both direct effect and indirect effect exist at the end. We identify time point 350 (on x-axis) as the benchmark point, since there is no more learning afterwards as shown in Figure 3. Therefore, we simulate the red line with decrease of 0.15 USD from time point 350 to represent the case of removal of direct effect of 0.15 USD in cash back promotion. Simulation result shows that fulfillment rate and online-pay rate are stationary from that point in both of black line and red line, which validates that drivers’ perceived attribute value is consistent with true value and the difference between red line and base line is only explained by the direct effect of sales promotion. Lastly we simulate the blue line which removes not only direct effect of 0.15 USD but also indirect effect from sales promotion before benchmark. To achieve that, we impose a negative sales promotion of -5 USD before the benchmark point, which almost inhibits any order fulfillment such that eliminates drivers’ learning through usage experience. We apply same sales promotion strategy (0.15 USD cash back reduction) as blue line after the benchmark, which indicates the direct effect of sales promotion is the same across blue and red cases. As a result, the difference between blue and red cases after the benchmark point will only be explained by past learning since it is the only difference between these two cases. Recall that the past learning is introduced by the difference of past sales promotion; we can attribute the difference as a consequence from indirect effect of sales promotion in the earlier time period. As we can tell, blue line is still following an increasing pattern, implying that drivers are still learning about the true attribute value of the app. This indirect effect will diminish with accumulation of drivers’ learning through more usage experience.
### 6.2 Estimating Effect of Sales Promotion on Passenger Side

Our model estimation results show that sales promotion on passenger side would have impact on outcome variables. However, the effect itself is not explicit given the non-linear function form, which leaves doubt on how strong such effect is compared with effect of sales promotion on driver side. We simulate outcome variables given adjusted passenger side sales promotion policy to visualize the effect explicitly. In addition, we simulate outcome variables with an identical adjustment but to driver side sales promotion to illustrate the strength of passenger side sales promotion effect comparatively.

We firstly simulate outcome variables of fulfillment rate and online-pay rate with the original sales promotion policy shown as black line. Given an adjustment of reducing 0.15 USD (1 RMB) on passenger side cash back, we simulate outcome variables represented by blue line. Furthermore, we apply the same adjustment but on driver side, shown as red lines. The left figure in Figure 5 shows that though existed, the marginal effect of passenger side sales promotion is very limited toward fulfillment rate compared with that of driver side sales promotion. With respect to online-pay rate (the right chart in Figure 5), since sales promotion on passenger side has direct effect on the use of online-pay, its overall marginal effect is more significant, but still small compared with that from driver side.

**Figure 5 Decrease Passenger Side Sales Promotion by 0.15 USD**

![Figure 5](Image)

To ensure the robustness of our findings, we specify a more powerful adjustment toward sales promotion to test whether similar result would maintain. In our experiment represented by Figure 6, we reduce the sales promotion by 1 USD on either passenger side or driver side. Compared with our findings in Figure 5, the marginal effects of sales promotion adjustment are more significant in both fulfillment rate and online-pay rate cases, and the conclusion that driver side effect is more prominent still holds in the new experiment. Note that our research is conditional on fixed orders generating rate due to data limitation; this description leads to managerial insights as put more weights on driver side to optimize the
overall performance of the app conditional on fixed arrival of orders. One thing worth noting is that passenger side sales promotion might also have impact on order generating process, and further impact overall platform performance. However, it is out of our research’s scope given the current information we have.

Figure 6. Decrease Passenger Side Sales Promotion by 1 USD

6.3 Optimizing Sales Promotion

In this session, we apply implications from model estimation results and the former policy simulation to optimize sales promotion strategy for TNC platform. Note that optimizing here doesn’t refer to manipulating policy to achieve optimal. Instead, we show directive heuristic policy-making method by following which we would improve performance of the platform. There might be an optimal point following our heuristic policy, but we are interested in the heuristic policy rather than a specific optimal point. Our objective consists of improving two dimensions: Online-pay rate and sales promotion cost. We focus on online-pay rate because it is our final outcome following the three stage sequential decisions, which reflects the overall impact of sales promotion. In addition, it is also the only stage associated with monetary transaction and revenue inflow. TNC who increases overall online-pay rate and reduces sales promotion cost would be better off with respect to profit maximization. The heuristic policy we use is based on our findings of indirect effect generated from learning and the comparison between effects of sales promotion on two sides. Recall that sales promotion of passenger side shows weaker effect compared with that of driver side, our first adjustment is to rebalance sales promotion between two sides with more weights on the driver side. Furthermore, we additionally rebalance sales promotion with regard to time. Specifically, we use intensive sales promotion at the very beginning of product introduction period to harvest more indirect effect, which is consistent with our claim that sales promotion has marginal indirect effect when learning happens.
Again we start with simulating a baseline by following the original policy shown as the black line in Figure 7. In this policy, sales promotion exists for both sides, with average of 1.47 USD for driver side and average of 1.58 USD for passenger side, and an overall sales promotion cost of 285,086 USD for 952 drivers. The first adjustment we make is to remove all sales promotion on passenger side and increase sales promotion on driver side by 0.1 USD, shown as the red line. The overall sales promotion cost decreases significantly to 116,610 USD, however, along with a significant loss of overall online pay usage shown as the space between black line and red line. The online-pay rates of black line and red line converge to similar level with accumulation of usage experience, implying similar direct effects of these two sales promotion policies, the difference between two lines is mainly explained by inadequate indirect effect at earlier stage.

Figure 7. Online-Pay Rate with Improved Sales Promotion Strategy

Simulated Online-Pay Rate Dynamics

To alleviate the loss due to inadequate earlier stage sales promotion, we increase sales promotion on passenger side to 4 USD during the first month since the app is released, which leads the overall cost to 186,010 USD. The amount of promotion per transaction, which we set as 1.5 times of the maximal value of original passenger side promotion, as well as the duration of the promotion might not be the optimal value numerically. However, here we only focus on a general pattern of our design, rather than the values themselves. From the blue line, we can find that intensive sales promotion works effectively to increase the overall online-pay rate by both direct effect and indirect effect, shown as the space between blue line and red line. The effects not only happen on the left hand side of the figure when increased sales promotion is imposed, but also apply to regions on the right hand side where indirect effect through learning still remains. However, the learning is still not addressed sufficiently since the online-pay rate
still falls below the original black line after 150 transactions, implying that the learning is not fast enough. This is because the learning on driver side is not fostered enough.

Our final policy is based on the blue line with a policy change of sales promotion of 3 USD for the first 50 orders on driver side. The intensity of this short-periodic promotion is the double size of the average in original case. The reason we only offers for 50 orders with a doubled sales promotion is that learning of accepting order and learning of cancelling order is comparably fast. From Figure 3, we can tell that the majority of learning of accepting orders finishes with 30 orders, and that of cancelling orders finishes with 100 orders. A more intensive sales promotion would lead to an even faster learning process, therefore we pick 50 orders as the duration. Again, those values are following heuristic rule rather than numerically optimization. The green line in Figure 7 represents the overall performance of this policy, with the space between green line and blue line representing the marginal effect of early sales promotion on driver side. The figure also shows indirect effect through the gap between blue line and green line after cumulative transaction number of 50 given a control of same direct effect, which addresses the importance of earlier period sales promotion. Our final policy envelops the original one (black line), indicating an overall improvement with respect to online-pay rate. In addition, the overall cost is 238,338 USD, much less than 285,086 USD in the original policy, indicating an overall better off in platform profit. Such findings explain why many TNC set intensive sales promotion at the very beginning.

One point worth noting is that even we improve earlier learning by imposing intensive sales promotion, it doesn’t necessary indicate that such promotion should last until the learning finishes. In fact, none of our simulations leads to a finished learning by the end of intensive sales promotion. This is because even learning would lead to higher perceived attribute value, its marginal effect diminishes with accumulation of experience, which implies there might be a specific point that the marginal effect of learning is inadequate to cover the cost incurred by extended heavy sales promotion. This finding is worth attention of policy makers.

7. Conclusion and Implications

TNC app platforms are trying to reduce their reliance on sales promotion to introduce new users, especially drivers. In our research, we find a solution for such question by understanding two mechanisms: first, how do new users form the initial preference of TNC apps; second, how does sales promotion make an impact on the formation of initial learning.

Our analysis shows that individual is conservative about adopting a new channel. TNC app users not only underestimate the attribute value of using an app, but also perceive the underestimated attribute value for passengers’ preference to use online pay function. As a result, drivers would form a comparably lower willingness to use and higher willingness to cancel a potentially “bad” order due to lower prior attributes and lower probability of receiving cash back bonus. This is consistent with our preliminary
results that both sides of users start with lower frequency of using the app functions, whereas the
cancelling rate is higher. It is also consistent with the risk-averse phenomenon from industry side that
individuals would always prefer the way they are familiar with, while reluctant to try newly introduced
alternatives such as IS enabled ones.

Usage experience plays a significant role in alleviating those biased uncertainty. With accumulation
of usage experience, users obtain adequate exposure to the true attribute value of new channel and
consistently perceive belief of passenger’s decision with diminishing uncertainty. The more usage
experience drivers have, the faster their perception converges to the true attribute. Given the estimation
results we obtain, we know that drivers would be more tolerant to accept orders, to fulfill orders and be
optimistic about being rewarded by cash back bonus once the learning process is finished. Such finding
supports the common industrial practice for enhancing usage experience during product introduction,
because it helps with consumer learning. It justifies the effort of enhancing usage experience through
different marketing tools, including sales promotion which is the example in our research context.

Our counterfactual analysis addresses sales promotion as an effective tool for user’s learning. As a
component in user’s utility function, sales promotion has effect in drivers’ decision of accepting order at
any time. Our result indicates that sales promotion happened in introductory period would have some
premium effect compared with that happened later. Other than direct effect of sales promotion on
contemporaneous drivers’ utility, earlier sales promotion would also have effect on decisions in later
period through early enhanced usage experience. In other words, compared with usage experience
happened later, early usage experience encouraged by sales promotion helps users’ learning, which has
impact on later period. This effect justifies the importance of early sales promotion for newly introduced
product, and it explains why most of TNC app platforms spend enormous efforts in sales promotion in
early stage. In addition, our finding shows the cross effect of two-sided sales promotion. Sales promotion
for passengers might have impact on decisions of drivers when drivers are rationally forward-looking and
when decisions of passengers would generate outcome that has impact on drivers’ earnings. Our analysis
further proposes a heuristic method to help app platforms improve their income while controlling their
cost for early sales promotion. The idea is intuitive: we fully make use of the earlier period which has
both direct and indirect effects. In addition, we rebalance the sales promotion for two sides by lowering
the weights for the less effective passenger side. Our simulation result shows that by applying this
method, TNC platform can save cost while keeping on increasing the overall online-pay rates. This tool
would not only work for TNC app platforms as the example in our case, ideally it can be extended to be
applied for all innovative business models introduced to the market. We hope that our econometric tools
can be converted into practical version, which would generate business value for those promising
industries.
Our paper has several limitations. First, the data available for researchers is limited. The introductory period of the product might indicate incomprehensiveness of data maintenance. For each transaction, our data do not observe information such as pickup locations, destinations, duration, as well as traffic routes, even though drivers might be able to partially obtain or infer such information. Such limitation restricts our investigation under the assumption of homogeneity of orders in terms of drivers’ learning process. Second, we take sales promotion as exogenous. Research considering strategic sales promotion might be interesting by allowing investigation of competition among different platforms and extending our learning framework to forward looking. Such research requires a dataset with a long enough period of enough variance of sales promotion in equilibrium. Our data only observes a period with several constant sales promotion amounts that each lasts for a long period. Individuals are well informed that in the coming moderate duration of period sales promotion is the same for all orders. Also the very introductory period casts doubt on equilibrium assumption. Third, we don’t account for network effects in our model. Network effects can be one component of learning signals, such that it would have impact on the speed of learning. However, due to the sparsity of sample and limited information, it is very difficult for us to figure out the “learning from network” mechanism and recover the network structure. All of the limitations can be cured and extended with additional datasets. Even though out of our scope, we believe that extension with further information will be promising, for example, drivers’ decision of location and route optimization and passengers’ willingness to generate an order.

In spite of the limitations, our paper has the following contribution. First, it is the first study modeling drivers’ decision process in the use of TNC app econometrically. It reveals how drivers’ decisions are influenced by TNC monetary rewards as well as their perceived passengers’ decision. Besides the direct effect from two-sided sales promotion, we also depict drivers’ learning from their usage experience that indirectly contributes to their overall use of the app. Our results help drivers to understand their learning of multiple attributes of TNC app. Second, we run policy simulation to see differential effects from different sets of marketing promotion designs. It generates managerial insights for runners with newly-introduced products about designing sales promotion in a more effective way. Our counterfactual analysis suggests an early with intensity sales promotion policy that not only enhances users’ willingness to use, but also is cost effective.

References


