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

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Abstract

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

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

1. **Introduction**

Information system never stops its expedition into reshaping traditional business. One recent progress of information system’s expedition is “transportation network companies” (we use TNC in short interchangeably), which is defined as “a service that does not own vehicles or employ drivers, and relies on software to connect passengers to rides”. Early runners of transportation network App include well-funded firms, such as Uber, Lyft, Hailo, OlaCabs, and Didi Dache. Information system creates value for different parties of stakeholders through the following formats. For taxi drivers, such app provides attribute value. Such attribute value includes functions like extended passenger pool and prior information about an order. Taxi drivers can select customers based on prior information about destination, tips and other requirements to match their preference of driving areas and routines, which might significantly reduce operations cost.

For taxi riders, TNC app provides value by simplicity and flexibility in transaction process. The most prominent functions are cancelling and online-pay. With cancelling function, passengers can easily adjust their preference based on updated information about ordered TNC taxis through apps and instant information about outside goods from other channels. Online-pay, on the other hand, simplifies business process during taxi riding period, saves time for both drivers and passengers, and allows passengers to be reached by sales promotion easily and effectively.
For app providers, TNC app provides a channel in which two-sided promotion can be conducted. Promotion for innovative online-to-offline experience goods is a common practice in industry during introduction period (Huet, 2015; Russel, 2015; Clifford, 2015). Majority of startup firms who run frequently purchased experience goods or services believe that it can convert user experience to “habit”. In other words, such sales promotion generates not only direct effect of increased demand, but also indirect effect in long term, in which customers fully perceive value of new products, and turn to be loyal customers.

In this paper, we answer two sets of questions to understand this business model: (1) Do taxi driver learn the value of App, and action of passengers through experiences? (2) How two-sided sales promotion makes impact on drivers’ propensity to use? How two-sided sales promotion interacts with drivers’ learning dynamically? And how should we design a better promotion to fasten drivers’ learning while being cost-savvy. We build a structural model about drivers’ decisions of accepting orders from App or not. By identifying exact conditional dependence among decisions of different sides of users in different, we apply structural model literature about two-sided decisions (Arcidiacono, 2005) and extend Bayesian learning model, in which we can handle multiple learnings. Our result quantifies drivers’ learning of app attribute value, passengers’ attribute value by using online pay, and passengers’ attribute value by committing to an order. Our counterfactual analysis identifies the direct effect and indirect effect of sales promotion, and proposes better strategy that fasten consumer learning while being cost-savvy.

2. Literature Review

Our research is related to the literature of dynamic between empirical consumer learning and sales promotion. In most setting of experience goods with adequate variation of prices, sale promotion is equivalent to temporary price cut. Consequently, very little academic research pays...
attention to tease out effect of learning from aggregate effect of sales promotion. There are exceptions as Erdem and Sun (2002). In their research, they investigate and find evidence of the spillover effects of sales promotion and advertising in umbrella branding of multiple products. In Chen et al (2008), they investigate another extreme case of sales promotion as permanent price cut for cigarettes.

In methodology, our research applies Bayesian learning model. Erdem and Keane (1996) firstly identifies customer learning about quality levels through experience and unobserved signals as advertising by applying Bayesian updating process. Due to its applicability with consumers’ choices under uncertainty, learning model is widely extended to account for more information, such as learning from observed signal (Erdem et al 2008); learning with different credibility (Zhao et al 2013); and with different weights, own preference for multiple attributes and variance of preference (Wu et al, forthcoming). But most researches allow only one aggregate to be learnt.

Our research is also the first paper investigating on-demand TNC Apps from information system perspective. Even though TNC Apps attract lots of attention from industry and media, there is limited research conducted on this topic. Rayle et al (2014) find that ride-sourcing complements traditional taxis and public transit by introducing younger customers, while competing with traditional taxis and public transit in the pie of traditional passengers. 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. 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. There is also some information system research around this topic. By using a study case of a taxi app, Tan et al.(2015) find that taxi app can use gamification to enable digital
disruption through situational and artifactual affordances approach. However, our paper is the first to propose a micro-level empirical model which depicts the business process.

3. Research Context and Data

Our data are from a TNC in China. It is now the largest mobile-app-based transportation network in China with over 100 million registered passengers, 0.9 million registered drivers and 5 million transactions per day.

The structure of this app is an ideal setting for studying the attribute value of app. Different from Uber in the United State who introduces more supply of transportation, this app only applies to existed taxis in the market due to the heavy regulations on taxi market in China. In other words, there is no new taxi introduced by app, and all app users in supply side are traditional taxi drivers. This setting helps to control effect, such as car characteristics and driver characteristics. The only exogenous changes in the setting are the introduction of the app and promotional activities with that. Each driver makes a decision of using app or 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 shows that every 655 people own a taxi in this city. This statistics is consistent with the popularity of App. Based on user experiences in our sample, orders arrive every few minutes. This condition erases our concern about endogeneity due to omitted demand when we model drivers’ decisions of taking App orders or traditional orders.

The typical process to use TNC app can be aggregated into 3 stages sequentially. Before it starts, the app provider announces the cash back plan to drivers and passengers. In the 1st stage, an order will be initiated by a passenger who needs a taxi with information of pickup location, destination and willingness-to-pay of tips. In the 2nd stage, drivers will decide on whether accept
an order from app or not, given the information above, and additional information of reward and expected cash back bonus from app provider. If drivers accept orders from app, passengers have two decisions to make in the 3rd stage. The first decision is whether to commit to the order accepted by a driver or not. Cancelling the order would happen if a passenger can get alternative transportation during the time while he/she is waiting. The second decision is to pay online or not conditional on the delivery is completed. This decision is conditional on functional attribute and cash back policy, since the cash back would be given to passengers and drivers only when online-pay is used.

Our data observes 50 drivers’ all transaction records from their registration in early May 2013 to late March 2014. We give up the very beginning of data until 12/27/2013 because there are significant function updates happening on those days, such that the true attribute value is not stationary. In total, we have around 26000 transactions. We observe the following 7 variables for each transaction as shown in Table 1 below. In addition, we show some aggregate statistics of our dataset in Table 2.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable Definition</th>
<th>Mean</th>
<th>Variance</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D^a_{it}$</td>
<td>Whether driver accept an order</td>
<td>0.9164</td>
<td>0.0766</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$D^c_{it}$</td>
<td>Whether an order is committed</td>
<td>0.8364</td>
<td>0.1368</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$D^{op}_{it}$</td>
<td>Whether online pay is used (cashback is given)</td>
<td>0.6449</td>
<td>0.2290</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$C^{cb}_{it}$</td>
<td>Cash back for passengers when use online pay</td>
<td>8.6200</td>
<td>2.7292</td>
<td>0.00</td>
<td>15.99</td>
</tr>
<tr>
<td>$B^{sb}_{it}$</td>
<td>Cash back for drivers when passengers use online pay</td>
<td>9.0410</td>
<td>8.6675</td>
<td>0.00</td>
<td>10.00</td>
</tr>
<tr>
<td>$B^{tip}_{it}$</td>
<td>Reward from passenger (tip)</td>
<td>0.4579</td>
<td>4.5012</td>
<td>0.00</td>
<td>20.00</td>
</tr>
<tr>
<td>$B^{sub}_{it}$</td>
<td>Subsidy for driver from App provider</td>
<td>0.1121</td>
<td>0.9236</td>
<td>0.00</td>
<td>50.00</td>
</tr>
</tbody>
</table>

Table 1
To show the dynamics of accepting order, committed order and onlinepay, we draw Figure 1 to show daily aggregate rate of the three variables with cash back policy for the same observation window. Black dots represent daily acceptance rate, blue dots represent daily online payment rate, and red dots show daily successful transaction rate. Comparing aggregate acceptance between day 30 to day 70, with that between day 90 to day 100, we find that even promotion policy for both sides are almost the same in those two periods, after the intensive promotion of the peak between day 70 to day 90, the same promotion policy can generate more accepted orders (between day 90 and day 100) than that generated before the peak (day 30 to day 70). This phenomenon indicates that drivers’ willingness to accept orders increase significantly by the promotion peak. One reasonable explanation for the increment might be that intensive users’ experiences lead drivers fully perceive the value of App, such that they are converted to be frequent users. We try to empirically identify this effect in the following models.

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median # of transactions for each driver</td>
<td>614</td>
</tr>
<tr>
<td>Mean # of transactions for each driver</td>
<td>594.6</td>
</tr>
<tr>
<td>Min # of transactions for each driver</td>
<td>138</td>
</tr>
<tr>
<td>Max # of transactions for each driver</td>
<td>1069</td>
</tr>
<tr>
<td># of transactions</td>
<td>29136</td>
</tr>
<tr>
<td># of accepted order</td>
<td>26700</td>
</tr>
<tr>
<td># of committed order</td>
<td>22881</td>
</tr>
<tr>
<td># of onlinepay order</td>
<td>18790</td>
</tr>
<tr>
<td>Pr (committed</td>
<td>accepted)</td>
</tr>
<tr>
<td>Pr (Onlinepay &amp; committed</td>
<td>accepted)</td>
</tr>
<tr>
<td>Pr (Onlinepay</td>
<td>committed)</td>
</tr>
</tbody>
</table>

Table 2
4. Model
Drivers make decisions on whether using app to receive orders or using natural passenger resource to receive orders, e.g. phone call, airport pickup, hotel pickup, passengers on the roadside, etc. We assume a driver $i$ at time $t$ will receive utility of $U_{it}^a$ if he/she accepts order from taxi app, and $U_{it}^o$ if not.

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

\[ U^a_{it} = D^s_t \times U^{suc}_{it} + (1 - D^s_t) \times U^{fail}_{it} + \epsilon^a_{it} \]

Here \( D^s_t \) is a dummy variable indicating whether transaction is successful, \( U^{suc}_{it} \) is the utility if the transaction is successful, which is expected to be positive. And \( U^{fail}_{it} \) is the utility if the transaction fails, expected to be negative. \( \epsilon^a_{it} \) represents an exogenous shock, which follows type I extreme distribution.

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

\[ U^{suc}_{it} = a_1 \times A^a_t + a_2 (D^p_t \times B^{cb}_t + B^{rip}_t + B^{sub}_t) \]

Here, \( A^a_t \) represents utility from attribute of app. The so-called attribute is consistent with literature of Bayesian learning here, which refers to the aggregate value generated by the product. \( D^p_t \) is a dummy variable indicating whether passengers use online payment. \( B^{cb}_t \) represents the bonus cash back for drivers from app providers when online payment is used. \( B^{rip}_t \) is reward from passengers and \( B^{sub}_t \) is the subsidy from app provider.

When transaction fails, we simply take the value of utility as a constant number \( C^{fail} \), which is expected to be negative. Take both cases together; we have utility of accepting the order as the following expression.
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At time \( t \), if taxi driver \( i \) receives utility from outside goods, he/she receives utility of \( U_{0it}^a \). We take the utility from outside goods to be an attribute level \( C^{\text{out}} \) plus a stochastic error term.

\[
U_{0it}^a = C^{\text{out}} + \epsilon_{0it}^a
\]

Before drivers make decision on whether using app to receive orders, they form expectation of the utility from two channels based on information updated to period \( t \), and pick the channel which maximize their instant expected utility. Before expectation forms, policy of cash back bonus for drivers and passengers, app subsidy and consumer reward is known. In addition, information till time \( t \), represented by \( I_{it} \), is known. As \( B_{it}^{\text{tip}} \), \( B_{it}^{\text{cb}} \) and \( B_{it}^{\text{sub}} \) are given before forming expectation, these three terms can be taken out of the expectation form. In addition, we note that the perception of attribute by driver is independent of the decision of commitment to an order by passenger. By some rearrangement following the property of conditional expectation, we have the following expression.

\[
E(U_{1it}^a \mid B_{it}^{\text{cb}}, C_{it}^{\text{cb}}, B_{it}^{\text{tip}}, B_{it}^{\text{sub}}, I_{it}) = \Pr(D_{it}^s \mid B_{it}^{\text{cb}}, C_{it}^{\text{cb}}, B_{it}^{\text{tip}}, B_{it}^{\text{sub}}, I_{it}) \times (a_{t} \times E(A_{it} \mid B_{it}^{\text{cb}}, C_{it}^{\text{cb}}, B_{it}^{\text{tip}}, B_{it}^{\text{sub}}, I_{it}))
\]

\[
+ a_{t} \times \Pr(D_{it}^p \mid B_{it}^{\text{cb}}, C_{it}^{\text{cb}}, B_{it}^{\text{tip}}, B_{it}^{\text{sub}}, D_{it}, I_{it}) \times (a_{t} \times E(A_{it} \mid B_{it}^{\text{cb}}, C_{it}^{\text{cb}}, B_{it}^{\text{tip}}, B_{it}^{\text{sub}}, I_{it}))
\]

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

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

\[
E(U_{0it}^a \mid B_{it}^{\text{cb}}, C_{it}^{\text{cb}}, B_{it}^{\text{tip}}, B_{it}^{\text{sub}}, I_{it}) = E(C^{\text{out}} \mid I_{it}) = C^{\text{out}} + \epsilon_{0it}^a
\]

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

4.1 Expected Attribute Level

We use Bayesian updating rule to model perceived attribute level. At the beginning of our observation, the driver has prior perceived value of app as $A_0$, which follows $N(A_0, \sigma_{A0}^2)$. It follows normal distribution, because the driver is uncertain about the app value, and $\sigma_{A0}^2$ captures the uncertainty level which is comparably large, whereas $A_0$ measures the mean level of the prior perceived value. The driver makes first-time decision based on prior information only, such that mean of first time perceived attribute is equal to the prior mean value $A_0$, and the perception of variance is equal to $\sigma_{A0}^2$. As drivers’ learning about attribute is conditional on experience only, we use $E(A_0 | I_{t0})$ to replace $E(A_{it} | B_{it}^{cb}, C_{it}^{cb}, B_{it}^{ti}, B_{it}^{sub}, I_{it})$ for simplicity.

$$E(A_{it} | I_{t0}) = A_0$$

Here $\sigma_{A_{t0}}^2$ is the variance of a driver i’s perception of mean attribute level at the very beginning. A driver updates perceived value and variance when they are better informed and when they learn the real attribute value of app. We assume the experience signal of app’s true value $A_t^e$ follows $N(A_t, \sigma_{At}^2)$. $A_t$ is the average experience value which equals true value, and $\sigma_{At}^2$ captures variance of signal. With more exposure to using app, driver’s perceived attribute value will be driven from prior value and finally converges around the true value. Also the uncertainty about attribute value declines, and perceived variance becomes smaller. Such serial changes in perceived value can be modelled through Bayesian updating rule, which depicts a concave
learning curve from prior mean and converges at true value, with the curvature governed by $\sigma^2_{A_0}$ and $\sigma^2_{A_1}$. Using a dummy variable $D^a_i$ to capture whether the driver $i$ use the app at time $t$, we can model our perceived attribute level and variance as follows.

$$\frac{A^e_i}{D^a_i} + E(A_{1(i-t-1)} \mid I_{i(t-1)})$$

$$E(A_i \mid I_i) = D^a_i \times \frac{\sigma^2_{A1}}{\frac{1}{\sigma^2_{A1}} + \frac{1}{\sigma^2_{A1(t-1)}}} + (1 - D^a_i) \times E(A_{1(i-t-1)} \mid I_{i(t-1)})$$

$$\sigma^2_{A_d} = D^a_i \times \frac{1}{\frac{1}{\sigma^2_{A1}} + \frac{1}{\sigma^2_{A1(t-1)}}} + (1 - D^a_i) \times \sigma^2_{A1(t-1)}$$

### 4.2 Probability of Receiving Committed Order

Commitment to a proposed order is the decision of a passenger. Drivers learn about decisions of passengers through experience, and form expectation over the decisions to calculate their expected utility. In other words, we model the drivers’ belief in passengers’ decisions. Even the drivers know $B^{cb}_i, C^{cb}_i, B^{tip}_i$ and $B^{sub}_i$, passengers’ knowledge set is limited to $C^{cb}_i$, cash back they gain if they pay online, $B^{tip}_i$, the reward they give driver to increase the accepting rate, and the attribute level of committing to an order. Note here that the attribute level here is different from the attribute level of app for driver. Here it means the driver’s belief of aggregate attribute for passenger of committing to an order. In addition, drivers know that $B^{cb}_i$ and $B^{sub}_i$ are independent on the probability of a committed transaction. Drivers’ belief in utility of passengers is conditional on $C^{cb}_i, B^{sub}_i$ and information till time $t$. We can simplify the expression as follows by pulling out independent variables.

$$E(U^s_{0it} \mid B^{cb}_i, C^{cb}_i, B^{tip}_i, B^{sub}_i, I_i) = E(U^s_{0it} \mid C^{cb}_i, B^{tip}_i, I_i)$$

$$E(U^s_{1it} \mid B^{cb}_i, C^{cb}_i, B^{tip}_i, B^{sub}_i, I_i) = E(U^s_{1it} \mid C^{cb}_i, B^{tip}_i, I_i)$$
If passengers are willing to wait, drivers expect passengers gain utility from three sources: attribute level for committed order, cash back from app if he/she keep on using online-pay, and paying extra reward. Among these three terms, $C^{cb}_i$ and $B^{sub}_i$ are known with certainty by drivers, and attribute is known by passengers but not fully known by drivers. Drivers need to learn about this value through their experience. Similar with model above, we model these learning processes following Bayesian updating rule with prior perceived value following $N(S_0 \mid \sigma^2_{s0})$, and signal following $N(S_1 \mid \sigma^2_{s1})$. The perceived attribute value in time $t$ for individual $i$ is $E(S_i \mid C^{cb}_i, B^{ip}_i, I_i)$. In terms of cash back and customer reward, we use additive form with weight to form the utility function. The latent utility follows the expression below.

$$E(U_{1it} \mid C^{cb}_i, B^{ip}_i, I_i) = d_1 \times B^{ip}_i + d_2 \times E(S_i \mid C^{cb}_i, B^{ip}_i, I_i) + d_3 \times C^{cb}_i + \varepsilon'^{i}_{1it}$$

If passenger is not committed, we assume that in driver’s belief, passenger will gain a systematic utility plus exogenous shock. As driver is used to traditional transportation form, he/she is well informed about the systematic component of utility for passenger. We model systematic component as a constant.

$$E(U_{0it} \mid C^{cb}_i, B^{ip}_i, I_i) = C^s + \varepsilon_{0it}$$

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

$$Pr(D^{c'}_i \mid C^{cb}_i, B^{ip}_i, I_i) = \frac{\exp(d_1 \times B^{cb}_i + d_2 \times E(S_i \mid I_i) + d_3 \times C^{cb}_i)}{\exp(d_1 \times B^{ip}_i + d_2 \times E(S_i \mid I_i) + d_3 \times C^{cb}_i + \exp(C^s))}$$
4.3 Probability of Online Pay

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

The information set about decision of using online-pay is exactly the same as that for receiving committed order, such that the modelling process is very similar to modelling probability of receiving committed order. To make the model concise, we don’t describe the full process again. We set $C^p$ as the systematic component for not using online-pay. $E(P_u \mid I_u)$ represents driver’s belief about perceived attribute value of using online-pay by customer, which updates following Bayesian rule with prior following $N(P_o, \sigma^2_{P0})$ and signal following $N(P_1, \sigma^2_{P1})$. We have the following result of probability of online pay.

$$E(U^p_{0i} \mid C^{cb}_u, B^{tip}_u, I_u) = C^p + \varepsilon^p_{0u}$$

$$E(U^p_{1i} \mid C^{cb}_u, B^{tip}_u, I_u) = b_1 \times C^{cb}_u + b_2 \times E(P_u \mid I_u) + b_3 \times B^{tip}_u + \varepsilon^p_{1i}$$

$$\Pr(D^a_i \mid D^{cb}_u, C^{cb}_u, B^{tip}_u, I_u) = \frac{\exp(b_1 \times C^{cb}_u + b_2 \times E(P_u \mid I_u) + b_3 \times B^{tip}_u)}{\exp(b_1 \times C^{cb}_u + b_2 \times E(P_u \mid I_u) + b_3 \times B^{tip}_u + \exp(C^p))}$$

4.4 Probability of Accepting Order

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

$$\Pr(D^a_i \mid B^{cb}_u, C^{cb}_u, B^{tip}_u, B^{sub}_u, I_u) = \exp(\Pr(D^a_i \mid C^{cb}_u, B^{tip}_u, I_u) \times (a_i \times E(A_t \mid I_u))$$
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\[ + a_2 (\Pr(D_u^c | D_u^s, C_{\mu_{u}}, B_{u}^{ip}, I_u) \times B_{u}^{cb} + B_{u}^{ip} + B_{u}^{sub}) + (1 - \Pr(D_u^c | C_{\mu_{u}}, B_{u}^{sub}, I_u)) \times C_{fail} \]

\[ \times \left(\exp(C_{out}) + \exp(\Pr(D_u^c | C_{\mu_{u}}, B_{u}^{sub}, I_u) \times (a_1 \times E(A_u | I_u) + a_2 (\Pr(D_u^c | D_u^s, C_{\mu_{u}}, B_{u}^{cb}, B_{u}^{ip}, I_u) \times B_{u}^{cb} \right. \\
\left. + B_{u}^{ip} + B_{u}^{sub})) + (1 - \Pr(D_u^c | C_{\mu_{u}}, B_{u}^{sub}, I_u)) \times C_{fail} \right) \]

\[ Llik = \prod_{t=1}^{T} \prod_{i=1}^{I} \Pr(D_u^c | B_{u}^{cb}, C_{\mu_{u}}, B_{u}^{ip}, B_{u}^{sub}, I_u) \times (1 - \Pr(D_u^c | B_{u}^{cb}, C_{\mu_{u}}, B_{u}^{ip}, B_{u}^{sub}, I_u))^{1-D_u^c} \]

5. Estimation Result

To identify three learning processes, we propose a 2-stage simulated MLE method to recover parameter. On stage 1, we recover parameters in modelling probability of online pay and probability of receiving committed order by using a standard Bayesian learning model with simulated MLE. On stage 2, in each time period when we simulate signal to form integration over signal variance, we also use updated believes of the probability that passengers will use online-pay conditional on the transaction is fulfilled, and of the probability that passengers will fulfill the order conditional on driver will accept the order to calculate the likelihood of driver’s decision of accepting the order. Then we simulate whether the transaction is indeed fulfilled and whether the transaction is ended with online-pay. After that, we update perceived value of three kinds of attributes by using Bayesian rule, and use the updated belief to calculate the likelihood in next time period. The simulation of action follows the conditional property among accepting order, committed to order and online-pay sequentially. And the policy function needs integration solved by simulation as well. Since our dependent variable is discrete choice variable, here we show the goodness of fit by plotting the aggregate rate of dependent variable across different individuals for the same cumulative number of transaction in Figure 2.
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Aggregate Accepting Rate Dynamics

![Graph showing aggregate accepting rate dynamics.](image)

Figure 2

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_0$</td>
<td>-5.9384633</td>
<td>0.47246106</td>
</tr>
<tr>
<td>$P_1$</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>$\sigma_{P0}$</td>
<td>10</td>
<td>-</td>
</tr>
<tr>
<td>$\log(\sigma_{P1}^2)$</td>
<td>3.5364492</td>
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<tr>
<td>$b_1$ (customer bonus)</td>
<td>0.4107051</td>
<td>0.08380525</td>
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<tr>
<td>$\log(b_2)$ (attribute learning)</td>
<td>-0.3083911</td>
<td>0.08577938</td>
</tr>
<tr>
<td>$b_3$ (consumer reward)</td>
<td>-2.5314013</td>
<td>0.14877448</td>
</tr>
<tr>
<td>$C^P$</td>
<td>-1.8649071</td>
<td>0.05464268</td>
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<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E</th>
</tr>
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<tr>
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<tr>
<td>$S_1$</td>
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<td>$\sigma_{S10}$</td>
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<tr>
<td>$\log(\sigma_{S1}^2)$</td>
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<td>$d_1$ (customer reward)</td>
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<tr>
<td>$\log(d_2)$ (attribute learning)</td>
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<tr>
<td>$d_3$ (customer cashback)</td>
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<tr>
<td>$C^S$</td>
<td>-2.1165239</td>
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Our result shows several interesting findings. We find that the learning process existed in all three expectations. The prior for app attribute is negative, which indicates undervaluation of TNC app by drivers at the very beginning. The prior for app attribute value for committed customers is positive, which indicates that the successful rate is overvalued. The prior of online pay is also negative, which indicates its undervaluation as well. All signal variances are pretty large compared with the scale of attribute level, indicating that drivers need to use it with comparably large quantity of experience to finally learn those attribute values.

We also identify parameters for two-sided promotion. Three forms of monetary bonus for drivers have positive effects on drivers’ decision of adoption as expected. Bonus policy for customers has impact on drivers’ decision through probability of receiving committed orders and probability of online pay. When cash back for consumers is high, both of above probabilities tend to be high, which increases latent utility for drivers to accept app based orders. We also identify a large negative parameter for uncommitted transactions. By rescale in monetary unit, such loss is equivalent to $5.59 cost for drivers. This indicates that cancelling order hurts drivers significantly, and might drive them to take outside goods.
6. Policy Simulation

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

6.1 Identify Indirect Effect of Sales Promotion

Indirect effect of sales promotion is implicitly proved by the existence of learning of driver in our model indicates. However, such effect is hard to measure directly by estimated parameters. We conduct a set of simulation here to show explicitly how much impact such effect existed for driver’s decision. We firstly simulate a baseline of driver’s decision across time period. By identifying a benchmark point in time horizon that accepting rate is stationary afterwards, which indicate that perceived value is converged with true value from that point, we simulate another case with removal of promotion policy from the benchmark point. Lastly, we simulate the third case with removal of promotion from the very beginning.
Figure 3
We aggregate the acceptance in daily level and show our result in figure 2. In the baseline case (Black), due to the fact that promotion existed from day 16080 till the end, both direct effect and indirect effect exists at the end. The red line represents the case sales promotion ends on benchmark point. Accepting rate of drivers is stationary from that point in both of black line and red line, indicating that drivers’ perceived attribute value is consistent with true value. The difference between red line and base line is only resulted from the direct effect of sales promotion. Blue line has no sales promotion from the beginning of our observation. When we look at the end of our window, even though sales promotions are removed in both of red line and blue line, there is still significant discrepancy. As we can tell, blue line is still following an increasing pattern, which indicates that drivers are still learning about the true attribute value of app. Since there are no direct effect in both of blue line and red line case, this discrepancy can be explained as indirect effect of sales promotion through learning.

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

We use the blue line case in the first part of counterfactual as our baseline. We use this case because our goal is to at least keep the same accepting rate after benchmark point where all sales promotions are removed. In figure3, we use black line to represent the baseline. This policy actually incurs cost of more than $60,000 for 49 drivers.

First new policy is simply to start our promotion earlier (Red line). By starting earlier, we can enhance drivers’ use experience earlier. Due to the general increasing trend of transaction amount per day as drivers uses more when learn more, period from the starting points actually have the fewest transaction amount, while incurred the most steep learning rate. It is obvious that it reach the same stationary accepting rate level at the end. Due to the decrease of transaction amount, our final total cost is around $50,000.

Our second policy further reduces the length of promotion by 10 days with the same starting point and promotion amount in red line case (Green line). We propose this policy because the red case shows that our accepting rate also converged at stationary level with promotion earlier when start earlier. It shows that it also reaches the stationary level once all promotions removed. Since we remove sale promotions in period where most condensed mass of transaction amount lies in, such policy result in a total cost of $35,000, which is significantly lower than red line.
Our third policy is “more intensive for shorter period” (Yellow line). Since a tried policy only with furtherly shortened promotion doesn’t reach the stationary level, we increase the amount of cash back for both drivers and passengers to encourage drivers to learn about the app more intensively. Our result shows that when we give customer cashback bonus at the maximal level of existed policy for all the time, and give 180% times of cash back for drivers, we reach the stationary point. Due to the increase amount for cash back, our cost saving is limited. Compared with last policy, we only save $1,000. If we just increase the amount of cash back for customer at the maximal level (Blue line), it saves us $10,000 thousand more than green policy, and our result is very close to stationary level.

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

7. Conclusion and Implications

In short, our analysis of TNC app yields several findings. We generally identify the economics mechanism behind drivers’ preferences for app-based orders versus outside goods. Our model shows the existence of multiple learnings when driver decides on using app or not.

By running counterfactuals, we identify the indirect effect of sales promotion in TNC setting. Our modified promotion policy shows that a shorter while more intensive sales promotion policy might performs better than alternatives in terms of cost. Such result explains why some TNC firms started even more intensive sales promotion in the recent days.
References


