# Understanding the Influence on Drivers' Recommendation and Review-Writing Behavior in the P2P Taxi Service

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***Abstract*—**The booming mobile business has been penetrating the taxi industry worldwide with P2P (peer to peer) taxi services, as an emerging business model, transforming the industry. Parallel with other mobile businesses, member recommendations and online reviews are believed to be very effective with regard to acquiring new users for P2P taxi services. Based on an empirical dataset of the taxi industry in China, this study aims to reveal which factors influence users' recommendations and review-writing behaviors. Differing from the existing literature, this paper takes the taxi driver's perspective into consideration and hence selects a group of variables related to the drivers. We built two models to reflect the factors that influence the number of recommendations and reviews posted on the platform (i.e., the app). Our models show that all factors, except the driver's score, significantly influence the recommendation behavior. Likewise, only one factor, passengers' bad reviews, is insignificant in generating more drivers' reviews. In the conclusion, we summarize the findings and limitations of the research.

***Keywords*—**Online recommendation, P2P taxi service, review-writing, word of mouth.

## I. Introduction

THE prosperity of the sharing economy greatly changes many industries and gives rise to substantial benefits for society and consumers [1]. The taxi industry is just one of the typical examples facilitated by such economic and technological impetus. With the aid of venture capitalists, the taxi industry is seeing a massive boom worldwide [2]. Nowadays, many drivers are enthusiastically using apps installed on their Smartphones to quickly target or respond to potential passengers to increase their operation efficiency. Compared to traditional approaches in which taxi drivers are either called directly or proactively cruise to find passengers, the P2P taxi service can help a driver to simultaneously and accurately position many passengers and destinations. This gives drivers the advantage of comfortably selecting a suitable passenger. As a result, both passengers and drivers can enjoy the convenience, as well as the novel experience, which is transforming the taxi industry dramatically. The sustainable development of the industry, however, is acknowledged to large extent to depend on the supply side's (i.e., drivers') contributions because on the demand side, the huge amount of passengers is greatly stirred by the generous subsidies from the P2P service providers. This results in the demand of passengers in this two-sided market widely surpassing supply. Currently, the penetration of various apps and social media fosters the consumption trend from online to offline [3]. Therefore, in this disparate market, higher efficiency can be achieved provided more drivers get involved. Taxi drivers not only play a vital role in the service process, they are also instrumental in acquiring more participants. Effective communications among drivers and between drivers and passengers will undoubtedly help recruit more potential users. Furthermore, mimicking the actions of consumers on shopping websites [4]-[6], taxi drivers also review and rate passengers, and share their experiences. Their reviews, functioning as the electronic word of mouth (WOM), are very helpful in improving service quality, and arouse the interests of potential users. Accordingly, member recommendation and online review, two effective approaches to increase market supply, have been intensively discussed and applied by practitioners and researchers. The former directly contributes to the increase of the supply base, while the latter recruits users by WOM. The extant research presents plentiful findings on user acquisition/recommendation, as well as online reviews. However, in the context of the P2P service, the factors that will influence drivers' recommendation and review-writing behavior are not explicitly revealed as yet. This paper aims to identify these factors to help the app operator effectively enlarge the business and underpin the quick development of the P2P taxi service.

Except for the practical value, the theoretical contributions of the study lie in two aspects. One is that the research investigates the quantity of recommendations and reviews made by the P2P service providers (i.e., drivers). Most of the existing research on users' recommendation primarily focuses on testing and measuring the effect of referral programs [7]-[10] or the design of recommendation systems [11], [12]. Research of online reviews comprises three streams: who to write [13], why to write [14] and what to write [15], [16]. In addition to revealing users' willingness, emotion and purpose on recommendations and review-writings, as reported in the existing research, the strength of engagement represented by the quantity of recommendations and reviews in the online community is worth investigating as well. However, the relevant research is far from being mature in P2P services with regard to recommendation and review-writing. Furthermore, how users on the supply side (herein, the drivers) behave (i.e., recommending and writing review) has not been sufficiently

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discussed for lack of data support [17]. This leaves a research space for us to take the perspective of service providers to analyze their online behavior. Towards this end, this research is a reasonable complement to the extant research in the area of recommendation and review-writing of P2P services.

The second contribution of the study is in the setting of P2P service to discover the relevant factors that influence drivers' recommendations and review-writing behavior. Different from the research in general online communities where the invitation is driven either by reward or by friendship [18]-[20], P2P service encourages incumbents to recruit new entrants by offering both immediate incentive (i.e., markup hereinafter) and self-gratification for their efforts. That is, for drivers of P2P services, recommendation is a kind of altruistic behavior [21], [22], not only a pure exchange. Even if an incumbent has no relationship with the entrants, he would like to invite them as more passengers could generate more value for the entire service platform. This is a good example of network externality, which explicitly interprets that the value of the platform primarily depends on the simultaneous increase of both passengers and drivers. As for online reviews written by service providers, they are supposed to play the same role as they do in online shopping. As a typical form of MGC (marketer-generated content), marketers' reviews have gained much attention recently as the interactions with UGC (user-generated content) reveal various outcomes [23], [24]. In this research, drivers' review-writing behavior is essentially indifferent from that of passengers in the context of P2P service so we can borrow relevant theories and research findings from the extant research on consumers' posting behavior and apply them to drivers' review-writing behavior. In addition, we also examined the influence of passengers' reviews on drivers' review-writing behavior. This angle, however, is rarely mentioned in the literature of MGC.

The rest of the paper is organized as the following. With respect to member recommendations and review-writing, Section II develops a group of hypotheses based on relevant literature. Section III builds three Poisson count models to test these hypotheses using an empirical dataset of the taxi industry in China. Section IV presents the empirical results, summarizes the findings and discusses the potential extensions of the research.

## II. Hypotheses Development

### A. Recommendation and Reviews

Online recommendations, as one of the most effective user acquisition approaches, is believed to be beneficial for inviters, invitees and the website (on most occasions, the inviter and the website are the same player) [20]. In this study, recommendation is defined as the number of passengers and drivers invited by an incumbent driver of the P2P taxi service in a time period. A recommendation is initiated by one of the members (i.e., driver user) of the app who sends an invitation code to those perspective users and asks if they want to join. Obviously, the role that the incumbents play is to advertise the app to potential users by promoting the advantages of P2P taxi service rather than rewarding or sharing the reward with the entrants. Once the app is installed and the first request is sent/taken, those entrants (i.e., passengers, as well as drivers), will be rewarded by the app operator. Although this mechanism is a bit different from the one discussed in the literature, it provides a unique view to observe what factors, aside from money, can drive the effectiveness of incumbents' recommendation. According to the literature [8], [6], [19], [25]-[28], six factors, markup, extra orders, driver's score, driver's source, passengers' reviews and discarded orders, are identified as effective influencers on the recommendation in this study.

Online review is one of the controversial but valuable research streams. Research on WOM reveals that nearly 70% of all buying decisions are influenced by WOM communications [29], which are also considered as the primary determinant in two-thirds of all industries [30]. Herein, review is defined as the number of review postings that an incumbent driver uploaded to the app platform in a time period. Nevertheless, not all apps allow passengers to browse every driver's review, as passengers generally have little time to choose drivers. The app in this research seals all drivers' reviews to passengers, who can only see how many passengers have reviewed the driver. The driver however can see all information about himself. In line with the recommendation, theories stemming from economics and social science will be responsible for the explanation to drivers' review-writing behavior. The factors affecting incumbent drivers to post reviews are supposed to be the same as those affecting their recommendations.

Referral reward programs and WOM are widely applied by traditional models and ecommerce platforms to the acquisition and retention of valuable customers. Research by Schmitt et al indicated that regarding marginal contributions and brand loyalty these customers acquired by referral program exceed customers from other channels [31]. These customers are more valuable for the website in both short- and long-term operation. Choi et al. confirmed that referred customers retain a much lower churn rate than those from the traditional channels [27]. Moreover, these presentees like to recommend new customers by actively posting the reviews or ratings. In the circumstance of the P2P taxi service, recommendation and review-writing should be under the umbrella of the theories on self-efficacy, self-enhancement and social network [32]-[36].

### B. Markup

Markup refers to a contingent amount of money paid by a passenger to a driver in the P2P taxi service when she hopes to be cared with a higher priority in some time (e.g., raining day). It is equivalent to the kind of reward often employed by marketers to offset consumers' switch cost or to tempt consumers to offer good reviews [9], [37], [38]. More precisely, it is actually akin to an all-pay auction that allows auctioneers to compete for the object only by one bidding. Markup is rare in the traditional taxi service so in P2P model it acts as a proxy of approval utility [6] and offers a monetary incentive and fun for drivers to help expand the passenger base. Drivers take the contingent auction as a novel and fun experience, which to some extent improves their sense of participation. This propensity is just so-called homeostase utility defined in [6]). The amount of markup is uncertain, largely depending on how anxious the passengers want to access the service at that time. In this investigation, the markup gap between the maximum and minimum exceeds 120 US dollar for a driver per month. Such a profitable business encourages drivers to enthusiastically commit to the new business model and also prompts them to make every endeavor to recommend the app to potential users. Accordingly, the demonstration effect should facilitate the recommendation among drivers.

As for review-writing, according to Cheung [21], people like to brag about themselves (i.e., egoistic motivation) or to catch eyeballs via social media when they experienced something special. Those drivers who are never rewarded previously by passengers most likely post their reviews after receiving the markup [39]. Such experience should spur them to share or express their appreciations. Hennig-Thurau et al invented two concepts, approval utility and homeostase utility to name this scenario [6]. Based on the above interpretations we pose the following two hypotheses:

**H1a.** The more markups a driver received, the more people he recommended to use the app.

**H1b.** The more markups a driver received, the more reviews he posted on the platform.

### *C. Extra Orders*

One of the obtrusive advantages of P2P taxi service is to drastically reduce drivers' idle driving time. Traditionally, taxi drivers' working time is not efficiently utilized to serve passengers. The P2P model in theory can sufficiently cram drivers' working time with enough orders if more passengers are recruited and then involve in the new service approach. Therefore, it is very critical for the P2P service provider to invite as many passengers as possible as the value that drivers received from the app depends on the number of passengers recruited in such two-sided market [40]. In reality, the invited passengers do use the app to request taxi service for its convenience according to our investigation. In turn, the extra orders contributed by recruited passengers enhance the value of P2P taxi service, hence resulting in more drivers championing the app and recommending to their friends. This just coincides with the reciprocity theory that states that if one's action benefits for others, they will pay back eventually [41]-[43]. In this circumstance, the recommendations not only benefit the passengers but also inflate the incumbent drivers' revenue when compared with the traditional service approach. Such a positive loop is supposed to generate more recommendations later on. Consequently, even without markup, drivers will still opt for recommendation to increase the value for themselves as well as the platform.

The factor, extra orders is also assumed to promote drivers to upload more review postings. Since more orders imply more income, one of the reasons for those drivers who are active in uploading review postings is the consideration of economic reward. Wang et al. pointed out that economic incentive is very critical to generate reviews, particularly the positive reviews [33]. Toward this point, extra orders should function as what markup does in motivating drivers to review and rate on this platform. In addition, altruistic consideration [21], [22] may be another reason. Those beneficiaries may like to propagate the amazing service model and to provide helpful information to other drivers, just as many online shoppers did. Based on the above interpretations we have the following hypotheses:

**H2a.** The more orders a driver acquired, the more people he recommended to use the app.

**H2b.** The more orders a driver acquired, the more reviews he posted on the platform.

### *D. Source*

Taxi drivers belong to different taxi companies, which form various sizes of social networks. Theory on social network posits that in a smaller network people will form much tighter ties (i.e., fewer intermediaries between any pair of nodes) and are more likely to share information or take consistent actions. Wirtz et al. and Ryu et al. indicated that when the referral has a close relationship with prospective users they are inclined to accept the service or product [18], [19]. In this case, a driver in a smaller taxi company would be more than willing to inform and persuade his close colleagues to install the app if he realized the value of P2P service. Another research by Duhan et al. shows that the recommendations by close people are more easily accepted if more perceptual knowledge is needed to evaluate the recommendation [26]. Luo et al. also pointed out that referrals' credibility can moderate the relationship of recommendation reliability and recommendation acceptance [25]. The smaller taxi companies are more easily to create close relationships that will contribute to generate more recommendations. Moreover, the higher degrees and density of the smaller network further amplify the quantity and scope of recommendations. In particular, the effect of WOM in the smaller social networks also facilitates recommendations. However, the smaller network is adverse to generate more reviews as the offline communication is more efficient [39]. Drivers in small taxi companies have many chances to communicate face to face so few of them rely on browsing reviews to get information. Hennig-Thurau unfolded the situation as the focus related utility [6]. Yoo echoed the phenomenon by examining travelers' review-writing behavior on TripAdvisor [44]. In addition, social connection and sense of belonging are conceived to matter in the dissemination of opinions in a social platform [21], [45]. In reality, suggestions, comments, and messages spread much faster in small companies. Thus, we propose the following hypotheses:

**H3a.** The smaller the taxi company a driver works for, the more people he recommended to use the app.

**H3b.** The smaller the taxi company a driver works for, the less reviews he posted on the platform.

*E. Passengers' Reviews*

Trusov et al. found that WOM can remarkably facilitate the increase of members of social websites [7]. Dierkes et al. believed that WOM greatly influences customers' purchase decision [41]. Therefore, just as the practice in other online communities or platforms, the app operator of P2P taxi service also encourages people to review and rate the service, the taxi companies and other people on the app. All users, whatever drivers or passengers can post their reviews on the platform. The factor, passengers' reviews, is defined as the number of reviews that a driver received from those passengers he served. Passengers' reviews comprise good reviews and bad reviews. Intuitionally, good reviews should play positive role in recruiting prospective users, whereas bad reviews would restrain drivers to do so. Those drivers who receive a large quantity of good reviews not only are satisfied with and champion the new business model but also are mightily motivated to invite more passengers. This is the so-called self-enhancement, which accounts for why passengers' good reviews give rise to more recommendations as well as reviews [28], [29]. Conversely, drivers burdened by many bad reviews may blame those passengers who rate them lower. This situation is very similar with that occurring to driver's score (see the last factor) so these unsatisfied drivers hardly recommend anybody, neither writing reviews [8], [13].

Passengers' courage (i.e., good reviews) arouses drivers' passion to upload more reviews as well. Such interactions are also found by Chen et al. [21] who indicated that movie audience remarkably increases their monthly review postings if they know how many people did so. Passengers' bad reviews, however, weaken drivers' self-enhancement, consequently undermining drivers' intention to post any reviews. In particular, the dissatisfied drivers may even divert to the opposite positon: posting more bad reviews as the response. Based on these explanations we deduce the following hypotheses.

**H4a.** The more good (bad) reviews a driver received, the more (less) people he recommended to use the app.

**H4b.** The more good (bad) reviews a driver received, the more reviews he posted on the platform.

*F. Discarded Orders*

As a novel business model, P2P taxi service has been inevitably obsessed by some problems. One of them is discarded orders, which to some extent impair the usefulness of the new service approach. In this investigation, discarded orders are defined as the number of orders discarded by a driver in a time period. The reasons to discard orders lie in the intentional and unintentional actions. The intentional discard happened when the driver either grasps a more profitable order before fulfilling the promised one or for some reason transfers the to-be-fulfilled order to another driver. The unintentional discard happened if passengers canceled the order or heavy traffic hinders the driver's quick arrival. It is acknowledged that too many discarded orders, particularly too many unintentionally discarded orders, might frustrate drivers' passion to offer P2P service, hence hindering them to recommend new users and write reviews. What is worse, they may think the new business model does not work at all. Hennig-Thurau [6] invented a concept, consumption utility, to name the scenario while Cheung employed altruistic motivation as the explanation [21]. The former shows that lower-quality product cannot bring value for consumers, who hence, will not recommend the product/service to other consumers. The latter states that without the enjoyment of helping people, users will not make recommendations. Both findings are applied to those drivers who choose to discard orders, no matter intentional or unintentional. On the other hand, too many discarded orders not only lead to the involved drivers being dissatisfied with the business model, but also imply the inefficiency of the app driveness. Kuester et al. confirmed that satisfaction/dissatisfaction is one of the necessary conditions for generating reviews [8]. Wangenheim et al. indicated that community driveness greatly influences users' participation (i.e., posting reviews) [9]. One of the obtrusive phenomena related to the driveness is that bad experiences will incur more bad reviews. This projection is also examined by Chen et al. [15] and Moldovan et al. [42], who found that lower-quality products incur more negative reviews. Regarding our research, drivers discarding many orders will be more likely upload reviews. In particular, if a driver discards unexpectedly more orders, according to the studies by Dellarocas [46], he likes to post the reviews to depreciate the value of the new business model. Upon that, we develop the following two hypotheses:

**H5a.** The more orders a driver discarded, the less people he recommended to use the app.

**H5b.** The more orders a driver discarded, the more reviews he posted on the platform.

*G. Driver's Score*

The driver's score is one of the most important indicators employed by the P2P service provider to not only evaluate a driver's service performance, but also show his value contribution to the platform. This indicator is figured out based on many factors, such as the driver's punctuation and passengers' complaints along the service process. Note that recommendation and review-writing are excluded from the consideration of scaling this indicator in this study. Higher score means higher passenger satisfaction and hence higher value that the driver contributes to the platform. Conversely, drivers with lower score may suffer for earning loss incurred by restricted service opportunities. Zeelenberg [13] asserted that lower satisfaction is positively associated with complaining behavior. This implies that the cluster of low-scored drivers is inclined to disappreciate P2P service and be reluctant to recommending people and writing reviews. Moreover, according to self-efficacy theory [34], [35], low-scored drivers may blame themselves for the poor performance and probably withdraw from the service fleet, let alone recommending. Hsu and Chiu analyzed a very similar situation where they showed that acceptance to an electronic service primarily depends on users' self-efficacy [36]. It is worth noting that the high-scored drivers do not definitely recommend more people because given the same conditions, whether or not to recommend may largely depend on those drivers' personalities.

Likewise, the low-scored drivers have little incentive to write reviews, as they are dissatisfied with the new business model. Their weak self-efficacy also affects their endeavor, hence hindering them from writing reviews, even browsing passengers' reviews. Moreover, if this cluster of drivers has a stronger sense of self-enhancement they are more likely to stay away from writing reviews.

Another speculation on driver' score is that the factor should relate to passengers' reviews and discarded orders. It is very straightforward that a large number of discarded orders inevitably result in lower scoring and in the same way passengers' bad reviews about an awful experience will definitely reduce the related driver's score. Cancelling orders is one of the main reasons for incurring passengers' dissatisfaction. The consequence of dissatisfaction is revealed by Zeelenberg [8] and Kuester et al. [13]. Likewise, bad reviews mean lower service performance, which in practice will tempt managers to confine the driver's service opportunities by decreasing his score. In contrast, passengers' praises certainly increase their drivers' score. Thus we posit the following hypotheses:

**H6a.** The lower score a driver is marked, the fewer people he recommended to use the app.

**H6b.** The lower score a driver is marked, the fewer reviews he posted on the platform.

**H6c.** The more orders a driver discarded, the lower the score he received.

**H6d.** The better (worse) reviews a driver received, the higher (lower) the score he is marked.

## III. Data and Result

In this study, we collected two datasets from a leading provider of P2P taxi service in China. The first dataset, spanning a month in 2015 encompasses the eight variables aforementioned and the second dataset comprises three other variables, city, registration time and source. Herein, city and registration time are treated as the control variables. City refers to which city (only two cities involved in this study) the participants are located. The indicator is coded as 1 and 2, with 1 representing big city and 2 the small city, respectively. Registration time is coded by the number of months that the driver gets involved the new business. Source indicates which taxi company a driver comes from before he embarks on the P2P service. This indicator is coded from 1 to 3, with 1 meaning the largest taxi company (more than 1,000 taxies) and 3 the smallest one (less than 100 taxies). Table I lists the statistics of the data.

In order to examine the proposed hypotheses above we build three models shown as the following:

$$\text{Rec} = \alpha_0 + \alpha_1 Markup + \alpha_2 Orders + \alpha_3 Score + \alpha_4 Source + \alpha_5 Gre + \alpha_6 Bre + \alpha_7 Dor + \varepsilon_1 \quad (1)$$

$$\text{Rev} = \beta_0 + \beta_1 Markup + \beta_2 Orders + \beta_3 Score + \beta_4 Source + \beta_5 Gre + \beta_6 Bre + \beta_7 Dor + \varepsilon_2 \quad (2)$$

$$\text{Score} = \gamma_{10} + \gamma_{11} Gre + \gamma_{12} Bre + \gamma_{13} Dor + \varepsilon_3 \quad (3)$$

where Rec, Rev, Gre Bre and Dor represent Recommendation, Reviews, Passengers' Good reviews and Bad reviews and Discarded orders, respectively. Estimation of the model is carried out using 2SLS (two-stage least square) regression so as to address the potential endogeneity issue of Score. The endogeneity issue arises when certain common unobservable factors (i.e., the market structure or traffic condition) affect both Recommendation or Reviews and Score simultaneously. In this case, Recommendation and Reviews are correlated with Score with regard to the error term, which makes the ordinary least squared (OLS) estimation to be biased. Table II shows the correlation of variables.

TABLE I
Descriptive Statistics

| Variable | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| Recommendation | 1.394 | 17.117 | 0 | 3257 |
| Reviews | 56.259 | 71.486 | 0 | 2775 |
| Markup | 23.491 | 49.093 | 0 | 2035 |
| Orders | 1075.027 | 1048.945 | 0 | 11181 |
| Score | 2535.002 | 2955.814 | 0 | 35243 |
| Source | 2.242 | 1.340 | 1 | 4 |
| Good reviews | 861.772 | 835.616 | 0 | 9118 |
| Bad reviews | 0.639 | 1.605 | 0 | 50 |
| Discarded orders | 47.847 | 63.200 | 0 | 1124 |
| Registration time | 52.577 | 19.747 | 9 | 98 |
| City | 1.276 | 0.447 | 1 | 2 |

TABLE II
Correlation

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1.Recommendation | | | | | | | | |
| 2.Reviews | 0.007 | | | | | | | |
| 3.Markup | 0.321 | 0.499 | | | | | | |
| 4.Orders | 0.110 | 0.330 | 0.195 | | | | | |
| 5.Score | 0.141 | -0.175 | 0.182 | 0.867 | | | | |
| 6.Source | 0.159 | -0.016 | -0.025 | 0.194 | 0.131 | | | |
| 7.Good reviews | 0.108 | 0.317 | 0.212 | 0.795 | 0.192 | 0.884 | | |
| 8.Bad reviews | -0.156 | 0.123 | -0.012 | 0.438 | 0.063 | 0.371 | 0.403 | |
| 9.Discarded orders | -0.080 | 0.374 | 0.030 | 0.077 | 0.493 | 0.159 | 0.705 | 0.480 |

To estimate the models, we firstly run a Poisson regression with respect to the instrument model (3) (i.e., the first stage in 2SLS) to obtain the estimated value of Score. Then we used the estimated value of Score in estimating the model (1) for Recommendation and model (2) for Review (i.e., the second stage in 2SLS). Note that the values of all independent variables are transformed by log function, so as to explicitly show their influence on dependent variables. Below are the empirical results of the analysis (see Table III).

TABLE III
MODEL RESULTS

| Variable | Model1 (Recommendation) | Model2 (Reviews) | Model3 (Score) |
|---|---|---|---|
| Markup | 0.084*** (0.007) | 0.905*** (0.001) | |
| Orders | 0.593*** (0.196) | 1.401*** (0.016) | |
| Score | 1.516 (0.020) | -0.052** (0.001) | |
| Source | 0.121*** (0.019) | -0.041** (0.002) | |
| Good reviews | 0.957*** (0.184) | 1.823*** (0.015) | 0.372 (0.008) |
| Bad reviews | -1.262** (0.012) | 0.055 (0.003) | -0.081*** (0.013) |
| Discarded orders | -0.019*** (0.021) | 1.184** (0.002) | -0.126** (0.007) |
| City | 1.116 (0.033) | -0.541 (0.005) | 0.016 (0.019) |
| Registration time | 11.862 (0.058) | -0.893** (0.003) | 0.090*** (0.015) |
| Intercept | -27.910** (0.128) | 3.991** (0.007) | 0.124*** (0.025) |
| Pseudo $R^2$ | 0.51 | 0.45 | 0.67 |
| LL | -121169.23 | -1076352.9 | -13257867 |

Note: 1. $^{**}p<0.05$, $^{***}p<0.01$; 2. Number of observations = 50473; 3. In parentheses are standard errors.

The results show that driver's Score has no significant influence on the Recommendation. Neither do passengers' Bad reviews on Review-writing and Good reviews on driver's Score. This implies that H6a is not supported by the data, whereas H4b and H6d are partially supported. The control variable, City is insignificant across three models, but Registration time obtains support in model2 and model3. The negative coefficients of the four variables, bad reviews, discarded orders, score and source confirm the correction of the corresponding hypotheses. Compared with model2, model1 is addressed by the factors more sufficiently in terms of Pseudo $R^2$.

## IV. DISCUSSION AND CONCLUSIONS

In this study, we identify a group of factors that significantly influence drivers' recommendation and review-writing behavior in the P2P taxi service. The empirical results indicate that the driver's score does not act as suggested, effectively affecting drivers' recommendation. This implies that those drivers, no matter how low they are scored, may still try to persuade as many as possible people to participate the new model because their self-efficacy stays away from such influence. The probable reason is that these low-scored drivers actually like the P2P approach very much, so they do not care about the score. Alternatively, the current scores do not represent those prudent drivers' real self-efficacy at all, as they take time to test the feasibility of the model (i.e., the so-called enactive attainment). If this is the case, the app operator should remove the function on scoring and in the meantime design a more effective mechanism to monitor the service quality. Likewise, the insignificant relationship between passengers' Bad reviews and drivers' Reviews is unexpected, as the finding is different from that reported by Moe and Schweidel who asserted that products receiving a greater number of reviews, no matter bad or good, tend to attract even more reviews [47]. We also examined the influence of passengers' total number of posted reviews on drivers' Reviews and ascertained their significance. One of the possible reasons can be attributed to the "one-sided community". Drivers knew that their review postings could not be seen by passengers so they might decrease the responses, even in the presence of many bad reviews from passengers. Such self-adjustment obviously mitigates the involved drivers' sentiments and thus scarcely affects their routine behavior. In addition, the total number of bad reviews is averagely incomparable with that of good reviews (the gap is about 150 times), so the affection resulting from bad reviews is mild. Thus, if the passengers' bad reviews are desired to effect on drivers' behavior, the app operator may take the mutual openness of the reviews into account.

The insignificance of the control variable, City shows that drivers' behavior is irrelevant with regard to the scale of the city. The ratios of population, the number of taxi drivers and driver users of the app in the two cities involved in this investigation are 2.7, 4.1, and 2.3, respectively. Nevertheless, the study results show that drivers in different cities are indifferent with respect to Recommendation and Reviews. This implies that the same recruitment strategy for the app can be applied anywhere. Another interesting finding is that registration time is negatively related to Reviews, meaning that the senior drivers have a reduced propensity to review. The signal warns the app operator that the incumbents need to be reactivated as soon as possible. Otherwise, the social value of the app for drivers will vanish, which eventually results in the business model suffering.

Finally, the three factors, Markup, Good reviews and Discarded orders exert stronger influence on Reviews than on Recommendation. In contrast, Recommendation is more sensitive to Orders and Source. Careful observation reveals that satisfaction primarily dominates the review-writing behavior, while usefulness underlies the recommendation behavior. For the app operator, how to upgrade drivers' satisfaction and meantime optimize the app's functions should be the future strategy.

The limitations of the research lie in two aspects. Firstly, we only have one-month data, which might be too short to sufficiently observe drivers' behavior. Actually, we are pursuing further support from the P2P taxi service provider now and preparing for rerunning the models, once more data is obtained. Secondly, the heterogeneous drivers should react to the factors differently regarding the recommendation and review-writing behavior. Therefore, the future research needs to be grounded on the clustered drivers.

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