Is Daily Deal a Good Deal for Merchants?
An Empirical Analysis of Economic Value in the Daily Deal Market

Chunhua Wu[1] Yitian (Sky) Liang[2] Xinlei (Jack) Chen[3]

Abstract

The daily deals platform has become an important format in the online-to-offline (O2O) business model. However, questions have been raised over whether merchants really benefit from participating in daily deals, with some evidence suggesting that a significant number of merchants are losing money from them. In this paper, we address this question by quantifying the economic value of daily deals using a structural approach. Using data from the Chinese daily deals market, we find that merchants not only profit from daily deals, but also take the biggest share of the economic value created by them. However, the gain mainly comes from future revenue, with merchants typically incurring a loss during the promotion period. We also find that competition among platforms increases the merchant's share of the economic value. Finally, we show that the competition in the current market is close to the optimal situation from a policy maker's point of view.

[1] Sauder School of Business, University of British Columbia. Email: chunhua.wu@sauder.ubc.ca.
[2] Sauder School of Business, University of British Columbia. Email: sky.liang@sauder.ubc.ca.
[3] Cheung Kong Graduate School of Business. Email: xlchen@ckgsb.edu.cn.

I. INTRODUCTION

The daily deals platform has been one of the fastest-developing Internet-based business models in recent years. Introduced in 2008, the concept of daily deals quickly attracted the attention of consumers and local merchants. By 2012, the leading platform, Groupon.com, had 41 million active users and reported gross revenue of $2.33 billion.[4] The same business model has been adapted quickly in emerging markets. In China, although the first daily deal platform was established two years later in 2010, the market has experienced tremendous growth. Over 200 platforms had emerged by 2012, leading to an overall market growth rate of nearly 100% between 2011 and 2012.

The daily deals platform is an important format in online-to-offline (so-called "O2O") business models. By offering collections of heavily discounted promotions that are valid for only a limited period of time, the daily deals platform can attract large numbers of consumers who purchase these deals online and then redeem them in the offline stores using the coupon. This appears to be an effective means of promotion for many offline merchants such as restaurants and salons, as they can enjoy not only a significant boost in the current sales period, but also increase future sales by attracting new consumers to their stores. This motivates the merchants to offer generous discounts on the daily deals platform. By allowing consumers to register and be informed about the deals, the platform creates value for consumers by helping them to purchase their preferred products at low cost. In general, daily deal platforms operate under a revenue-sharing model with the merchants by extracting a commission from each realized transaction.

However, whether merchants really benefit from daily deals has been questioned. For example, Dholakia (2010) surveyed a sample of merchants and found that one third of them had not profited from Groupon promotions, because of the combination of the deep discounts offered

[4] Groupon's online 2012 fiscal year announcement: http://investor.groupon.com/releasedetail.cfm?releaseid=743818

to consumers and the high commission extracted by the platform. For example, in the US market, merchants often offer 50% discounts in daily deals promotions (Li, Shen and Bart 2014), and the platform extracts an additional 40–50% of the sales revenue (Dholakia 2012), suggesting that merchants earn little to nothing from daily deals sales. This uncertainty, coupled with continuing strong public interest and intensive media attention, has generated intense debate over whether the business model is sustainable in the long term (Wheeler 2011).[5]

In this paper, we address this question by quantifying the economic value extracted by each party (consumer, platform, merchant) in the daily deals market. We construct a structural model that incorporates the merchants' platform choice, and the pricing decision, by merchant (discount rate) and by platform (commission rate). Specifically, we consider both the merchants' short-term and long-term gains from the daily deals. For example, merchants could use daily deals as loss-leader advertising to attract new customers for product trials. Although potentially suffering a loss in the short term, they could attract future revenue from returning customers and consumer word-of-mouth.

Another interesting question is how market concentration affects the share of the economic value among parties in the market. For instance, in the United States, Groupon and LivingSocial collectively represent nearly 90% of market share (Li, Shen and Bart 2014). Due to the lack of competition, in the early days they charged a fixed commission rate of around 50% and 40%, respectively. Only in the recent quarter have their commission rates been reduced, due to increased competition.[6] In contrast, the daily deals market in China has experienced fierce competition from the beginning, hence platforms have to choose the commissions for each daily

[5] https://hbr.org/2011/08/groupon-doomed-by-too-much-of.
[6] See: http://seekingalpha.com/article/2385935-groupon-q214-dont-throw-in-the-towel-yet.

deal carefully and strategically, rather than stay at fixed rates. To incorporate this, our model also considers competition between platforms.

We use data from the Chinese daily deals market in our model. With the significant, competition-driven variations in commission and discount rates, we use data from the Chinese market to identify how competition among platforms affects the distribution of economic value. However, data limitations raise some empirical challenges in the analysis. First, although we are able to observe a merchant's discount rate, we do not know the platforms' commission rates, thus we lack key information regarding the platforms' strategic choices. Second, there is a selection issue in the data: we observe the discount and sales when a merchant collaborates with a specific platform, but not had the merchant chooses a different platform, which is necessary to model a merchant's platform choice.

To address these challenges, we rely on the equilibrium constraints derived from the game to quantify the unobserved discount and commission rate. To make the estimation feasible, we focus on the four largest daily deals platforms in the Shanghai market. In addition, we limit our analysis to a subset of merchants that contribute the most value to the platforms. These merchants are the top sellers in the market and account for nearly 40% of market sales.

Our results show that merchants not only profit from the daily deals, but also take the biggest share of the economic value created by them. However, daily deals promotions serve as "loss-leader" advertising for the merchants. Therefore, while they typically incur losses during the promotion period, this is compensated for by future profits. Using counterfactual analysis, we further show that anti-competitive policies, such as a fixed-commission policy, will benefit the platforms but at a cost to the merchants. If the merchants were stripped of their pricing power on discounts, the market would become worse for all parties. Because both fixed commissions and fixed discounts are features of the US market, our analysis provides insights for policy makers. Finally, our counterfactual analysis shows that the policy makers or regulators could only increase the total welfare by less than 1% compared with the current market, which suggests that the level of competition in the current market is close to optimal from a policy maker's view. This implies that the current market has a fairly healthy market structure.

This paper contributes to the growing literature on the daily deals market, and directly addresses the economic value of this business practice. The literature is generally silent on the question of value, with the exception of Dholakia (2012), who examined whether deal merchants can make profit in a certain timeframe using a survey method. Our approach differs from that of Dholakia (2012) by using secondary data to directly quantify the economic value of daily deals based on the equilibrium behavior from a theoretical model. From the managerial perspective, our results shed light on the potential costs and benefits of doing daily deals promotions for marketing managers of local businesses. Our policy simulations also generate practical insights for platforms and policy makers that will help them to understand the nature of competition in this industry.

The remainder of the paper is organized as follows. In the next section, we review the relevant literature. We describe the institutional background and data in Section III. We present the model and estimation method in Section IV, report our findings in Section V, and conduct the policy analysis in Section VI. Finally, in Section VII, we conclude with a discussion of our findings and suggest future research directions.

II. LITERATURE REVIEW

This paper is closely related to two streams of literature in marketing and economics. First, there is a growing body of literature on the phenomenon of daily deals promotions, along with the rising popularity of the business practice. Jing and Xie (2011) were among the first to theoretically examine the nature of group buying and explore when it is optimal to use a group-buying mechanism compared to individual selling and referral programs. In another theoretical work, Edelman, Jaffe and Kominers (2011) looked at the profitability of daily deals promotions from the perspective of the underlying mechanisms: price discrimination and advertising. On the empirical side, Dholakia (2012) explored the performance of daily deals using survey studies across multiple years. The work was constrained by the sample size, and the separation between short-term and long-term profitability was addressed in less detail than in this paper. Using another survey study from consumer responses, Dholakia and Kimes (2011) looked at consumers' perceptions of daily deals, across both heavy-user and non-user groups, and found no evidence of daily deals fatigue. Other works have explored consumers' herding behavior in buying daily deals (Li and Wu 2013), the effect of daily deals promotions on Yelp ratings (Byers, Mitzenmacher and Zervas 2012, Hoban 2013), and dynamic customer-poaching behavior between platforms (Kim, Lee and Park 2013). We contribute to this stream of literature by using secondary data to directly address the economic value of daily deals based on the equilibrium behavior derived from a theoretical model.

Second, our research is closely related to the literature on channel pricing and two-sided platform competition. On the theoretical side, following McGuire and Staelin (1983), a large body of literature (Rey and Stiglitz 1995, Iyer 1998, Desai, Koenigsberg and Purohit 2004, Dukes, Gal-Or and Srinivasan 2006) has investigated the channel-pricing problem in various contexts. On the empirical side, Sudhir (2001) developed a structural model to examine alternative models of manufacturer-retailer interaction. Bonnet and Dubois (2006) modeled nonlinear contracts (i.e. two-part tariffs and resale price maintenance) between manufacturers and retailers. Berto Villas-Boas (2007) also studied vertical interactions among multiple manufacturers and multiple retailers. While this stream of the literature focuses on pricing decisions in the channel, it barely discusses the choice of channel. Our work differs from this literature in that we discuss both the pricing decision and the channel choice (i.e. which platform to collaborate with). In the two-sided platform-competition literature (Armstrong 2006, Caillaud and Jullien 2003, Rochet and Tirole 2003, 2006), the focus has been on the pricing decisions set by platforms, usually taking the other side of the market as the price-takers. Our work differs from this by treating both platforms and merchants as strategic decision makers. Finally, Kim, Lee and Park (2013) examined the dynamic competition in daily deals from a customer-poaching perspective. We contribute to this literature by proposing and estimating a non-trivial model that accounts for both revenue sharing and pricing decisions in a channel, as well as platform competition.

III. INSTITUTIONAL BACKGROUND AND DATA

To fully illustrate the dynamic and competitive incentives in the daily deals market, we analyzed the Chinese market. The first major Chinese daily deals platform, Meituan, was established in March 2010. Inspired by the success story of Groupon in the US, thousands of daily deals platforms emerged in China in less than a year. Since then, although the market has been growing steadily over the years, with an estimated annual growth rate of more than 100% between 2011 and 2012,[7] fierce competition has driven most of the platforms out of the market.

To survive in the market, platforms compete fiercely to attract the best deals to their websites. They typically set up a business development team to contact local merchants and to negotiate the commission rates. Typically, there are significant differences in the market potential of these deals because the inherent popularity of the merchants varies significantly. For example, in the restaurant category, the revenue that the platform can make from the best deal is on average 3.55 times that of the second best. On each day across platforms, the sales volume of the largest deal in the market is 3.14 times that of the second largest, and accounts for 39% of the sales in the entire market. Therefore, platforms will compete to host these star merchants on their websites.

We acquired data from a deal aggregator website that tracks the deal performances from the major daily deals platforms. The data contain detailed information on each daily deal, including the platform, merchant, product category, regular price, discount rate, and sales. For each merchant, we also collected customer reviews from the largest consumer review website in China. Our data contain complete daily deals information for more than 400 major daily deals platforms on the five largest markets from May 2010 to January 2013.

To bring our scope of analysis to a manageable level, we mainly focus on the restaurant category in the Shanghai market. The restaurant category is the largest category in terms of transaction revenue, and Shanghai is the largest daily deals market in China. Hundreds of daily deals platforms competed in the marketplace during the data period. However, the market is quite concentrated, and a few platforms consistently occupy the majority of the market share. We focus on the top four platforms, Meituan, Lashou, Nuomi and Dianping Tuan, which account for

[7] http://tech.qq.com/zt2011/cnnic28/.

nearly 80% of market share. These big early entrants in the market have grown steadily over the years. Despite frequent entries and exits in the market, these four platforms have collectively retained a significant market share in the restaurant category. We provide some basic information on these platforms in Table 1.

On the merchant side, we focus on the most valuable deals in our data, i.e. the largest deal in the market on each day. These merchants contribute most of the revenue to the platforms. By studying these merchants, we capture the key part of the daily deals market. Most importantly, this dramatically simplifies our analysis. In negotiating daily deals, a typical scenario will involve multiple merchants negotiating with multiple platforms at the same time. Each merchant typically chooses only one platform at a given time, but a platform can choose more than one merchant at the same time. Although the data indicate when a deal was promoted, they do not indicate when the contract was signed. Therefore, we cannot identify the set of merchants who negotiated at the same time. Interestingly, the empirical evidence suggests that platforms do not treat every merchant equally. Typically, a platform will invest more resources to feature the star merchants. The featured deal will occupy a significantly large space on the website's front page, and will be the only deal promoted through emails to subscribers. This suggests that platforms try to get star merchants on board, and treat them separately from the rest during negotiations. Therefore, we assume that platforms compete to get star merchants on board, and this is independent from decisions made regarding any other merchants. Given this assumption, we consider how platforms compete to get a star merchant, simplifying the multiple merchant and multiple platform game into a single merchant and multiple platform game.

After removing incomplete information, our final sample consists of 482 of the largest deals on the market. We report the descriptive statistics in Table 2. On average, the merchant discount is 49%, which is close to the US level. However, there is a huge variation across deals, with a first quartile of 37% and a third quartile of 60%. This contrasts with the standard fixed rate in the US market. The mean revenue of the featured deal is $53,400[8] and the list price is $16. We do not know the commission rates, but estimate them in our structural model.

IV. MODEL AND ESTIMATION

In this section, we present our model, the identification strategy, and estimation method. We assume that major platforms compete for each star merchant. At the beginning of each period, a star merchant decides to do a daily deals promotion and expresses its interest to all of the platforms. Each platform states its commission, taking into account the merchant's reaction. The merchant then chooses which platform to work with and decides the optimal discount. Then the demand is realized, given the price and discount. We now discuss the details of our model in reverse order.

Consumer Demand Model

We start with how consumers make purchase decisions on daily deals. We assume that there are M consumers in the market. When facing a star deal i on platform j at time t, the indirect utility of consumer h from buying the daily deals coupon is

$$u_{hijt} = \alpha_{jt} + v_{it} + \gamma \cdot \lambda_{ijt} p_{it} + \epsilon_{hijt}, \tag{1}$$

where $\alpha_{jt} = \varphi_{\alpha}\left(t, \beta_j^{\alpha}\right)$ captures the attractiveness of the platform, which could evolve over time, and $\varphi_{\alpha}(\cdot)$ is a flexible function of t. $v_{it} = X_{it}\beta^{v} + \xi_{it}$ captures the attractiveness of the merchant, which depends on the observed merchant attributes X_{it} and the unobserved merchant characteristics ξ_{it}.[9] p_{it} is the regular price of the merchant, and λ_{ijt} is the discount for the daily

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[8] The exchange rate is set at US$1 equals 6.15 RMB throughout the paper.

[9] Note that ξ_{it} is observed by all platforms but not by the econometrician.

deal. Consumers pay $\lambda_{ijt} p_{it}$ when purchasing the deal coupon. Finally, γ measures consumers' price sensitivity to the product category. Given that there could be multiple deals offered at the same time across various platforms, we assume that the purchase decision of the star deal on a given day is independent from the decisions for other deals. This is justified by our earlier finding of the significant market share captured by star deals.

The utility of the outside option is assumed to be $u_{h0jt} = \epsilon_{h0jt}$. Both of the random shocks ϵ_{hijt} and ϵ_{h0jt} are assumed to follow the Type I Extreme Value distribution. Given the distributional assumption, we have the market share for deal i on platform j as

$$s_{ijt} = \frac{\exp\left(\alpha_{jt} + \nu_{it} + \gamma\lambda_{ijt} p_{it}\right)}{1 + \exp\left(\alpha_{jt} + \nu_{it} + \gamma\lambda_{ijt} p_{it}\right)}. \tag{2}$$

<u>Merchant</u>

A merchant could generate both short- and long-term profits from the daily deals promotions, which is reflected in the following equation:

$$\pi_{ijt}^{V}\left(\lambda_{ijt}\right) = M \cdot s_{ijt} \cdot \left[\left(1-\delta_{ijt}\right)\lambda_{ijt} p_{it} - c_i p_{it}\right] + \tau_{ijt} \cdot M \cdot s_{ijt} \cdot p_{it}\left(1-c_i\right) + \omega_{ijt}. \tag{3}$$

The first component captures the current profits from the promotion, where δ_{jt} is the commission rate, and c_i is the percentage cost of the goods or service relative to the regular price. The profit equals sales times the profit margin, in which we need to subtract the platform share and the product cost of each deal. We modeled the cost ratio c_i in a deterministic way, i.e. $c_i = \frac{\exp\left(X_i \beta^c\right)}{1+\exp\left(X_i \beta^c\right)}$. The second component captures the effect of future profits, which could come from returning consumers or customers who are generated by word-of-mouth, and who will purchase at full price. The sales from future periods need not be shared with the platform, thus the merchant will have a significantly higher profit margin. Here, τ_{ijt} captures the magnitude of returning purchase compared with promotion period sales, and is modeled as $\tau_{ijt} = \varphi_\tau\left(t, \beta_j^\tau\right) + \epsilon_{ijt}^\tau$, where $\varphi_\tau(\cdot)$ is a flexible function of t and $\epsilon_{ijt}^\tau \sim N\left(0, \sigma_\tau^2\right)$ with $corr\left(\epsilon_{ijt}^\tau, \epsilon_{ikt}^\tau\right) = \rho$. We call τ_{ijt} the "future demand multiplier". We assume that the deterministic part in this function is common knowledge to all of the platforms and to the merchant, while the stochastic part ϵ_{ijt}^τ is private information of the merchant. Finally, ω_{ijt} captures the synergy between the merchant and the platform, which is also the merchant's private information. We assume that this shock follows a Type I Extreme Value distribution with a mean of 0 and variance of σ_ω^2.

Given a platform to cooperate with, the merchant will choose the optimal discount level to maximize the expected total profits generated in both the short and long terms. From the first order condition, we can analytically derive a closed-form expression for the optimal discount policy as shown below. We provide the details of the derivation in Appendix A.

$$\lambda_{ijt}^* = \frac{c_i}{1-\delta_{jt}} + \frac{\tau_{ijt}(c_i - 1)}{1-\delta_{jt}} - \frac{1}{\gamma p_{it}} - \frac{1}{\gamma p_{it}} W\left(\exp\left\{\frac{\gamma p_{it} c_i}{1-\delta_{jt}} + \frac{\tau_{ijt}\gamma p_{it}(c_i - 1)}{1-\delta_{jt}} + \alpha_{jt} + \nu_{it} - 1\right\}\right), \tag{4}$$

where $W(\cdot)$ is the Lambert W function.

The merchant will choose the platform that could generate the highest expected profit from the promotion. From the distributional assumptions, the probability of choosing platform j (among K platforms) on day t is

$$\mathcal{P}_{ijt}(\delta_t, \tau_{it}) = \frac{\exp\left(v_{ijt}\right)}{\sum_{k=1}^K \exp\left(v_{ikt}\right)}, \tag{5}$$

where $\delta_t = \{\delta_{kt}\}_{k=1}^{K}$ is the set of commission rates set by the platforms, $\tau_{it} = \{\tau_{ikt}\}_{k=1}^{K}$ is the set of discount rates that would have been set by the merchant if collaborating with each platform, and

$$v_{ijt} = \frac{1}{\sigma_\omega}\left\{M \cdot s_{ijt} \cdot \left[\left(1-\delta_{ijt}\right)\lambda_{ijt} p_{it} - c_i p_{it}\right] + \tau_{ijt} \cdot M \cdot s_{ijt} \cdot p_{it}\left(1-c_i\right)\right\}. \tag{6}$$

Because ω_{ijt} is unobservable by both the platforms and the researchers, equation (5) presents both the likelihood of observing the platform choice made by the merchant and the platform's belief (at the time of announcing its commission rates) that the merchant will choose it from among all of the platforms.

<u>Platforms</u>

Platforms compete to attract the merchant by offering attractive commissions. They differ in their ability to generate both short- and long-term profits for the merchant, and consequently their ability to charge a higher commission rate. Because the platforms do not fully observe the future profit effect τ_{ijt}, their expected profits from hosting a merchant is

$$\pi_j^P\left(\delta_t\right) = E_{\epsilon_{it}^\tau}\left\{\mathcal{P}_{ijt}\left(\delta_t, \tau_{it}\right) \cdot \left[M \cdot s_{ijt}\left(\lambda_{ijt}\left(\delta_{jt}; \epsilon_{ijt}^\tau\right)\right) \cdot \delta_{jt} \cdot \lambda_{ijt}\left(\delta_{jt}; \epsilon_{ijt}^\tau\right) \cdot p_{it}\right]\right\}, \tag{7}$$

where the expectation is taken with respect to $\epsilon_{it}^\tau = \left\{\epsilon_{ikt}^\tau\right\}_{k=1}^{K}$, which is the set of private values in the future demand multiplier τ_{it}. The equilibrium profile δ_t^* must satisfy[10]

$$\pi_k^P\left(\delta_{kt}^*, \delta_{-kt}^*\right) \geq \pi_k^P\left(\delta, \delta_{-kt}^*\right),\ \forall \delta \neq \delta_{kt}^*,\ \forall k. \tag{8}$$

<u>Estimation Strategy</u>

The set of parameters to be estimated is

$$\Theta = \left\{\beta^\alpha, \beta^\nu, \gamma, \beta^c, \beta^\tau, \sigma_\omega^2, \sigma_\tau^2\right\}. \tag{9}$$

[10] We assume that a Nash equilibrium to this pricing game exists, but check numerically whether our final estimates are consistent with the existence of an equilibrium as well as uniqueness (as in BLP 1995).

We now discuss the sources of identifications in our model. First of all, the parameters embedded within the demand side equation, i.e. $\left(\beta^{\alpha}, \beta^{v}, \gamma\right)$, are identified from the variations in the unit sales, i.e. s_{ijt} of different daily deals promotions based on the variations in the merchant characteristics. Second, based on the identified consumer demand parameters, the information of the discount level λ_{ijt}, as solved in equation (4), gives us the estimates on $\frac{1}{1-\delta_{jt}}\left[c_i + \tau_{ijt}\left(c_i - 1\right)\right]$. As we pointed out, δ_{jt}, although not observed, is implied by the equilibrium conditions in (8). Thus, the equilibrium solution is a nonlinear function of c_i and τ_{ijt}. The nonlinear functional form of c_i and τ_{ijt}, i.e. the interactions, helps us to identify the parameters of β^{c} and β^{τ}, as well as the variance in the residual term σ_{τ}^{2} from the equilibrium condition of the optimal discount rate. On top of the nonlinear functional form, we also exploit a key feature in our context to separately identify cost and the future demand multiplier. The percentage cost is unlikely to depend on platform characteristics (i.e. c_i is modeled as a function of merchant characteristics), whereas the future profit multiplier is platform-specific. Therefore, variations in discount rates across platforms also help us to separately identify these two parameters. As pointed out earlier, we do not observe $\lambda_{ij't}$, i.e. the optimal discount rate merchant i charges had it chosen platform j in period t. This creates a selection problem in equation (4). Specifically, merchant i may choose platform j because of a relatively large ϵ_{ijt}^{τ}. In other words, although the mean of ϵ_{ijt}^{τ} is 0, conditional on merchant i choosing platform j, the conditional mean of ϵ_{ijt}^{τ} is no longer 0. Instead, it is greater than 0. To control for the selection problem, we utilize the variation in the choice outcomes d_{ijt}, which helps to identify the last parameter, σ_{ω}^{2}. Specifically, as equation (6) shows, σ_ω^2 scales the expected profit and determines the platform selection probability.

We estimate the consumer demand model using the Generalized Method of Moments (GMM). To control for the price endogeneity, we use the average discount rates of daily deals promotions in other markets in the past week as the instrumental variable. The average discount levels are likely to be correlated across markets because the set of major platforms the merchants are dealing with are identical across the markets. However, the average discount level in a different market will not correlate with the merchant-specific characteristics in the focal market. This makes the average discount level from other markets a good instrument.

Given the demand estimates, we next estimate the supply side parameters using the simulated maximum likelihood method (SMLE). The log-likelihood function is

$$L(\Theta)=\sum_{t=1}^{T} L_t(\Theta). \tag{10}$$

On a specific day t when the merchant i chooses platform j to promote the daily deal, we observe $Y_t=\{\lambda_{ijt}, d_{it}\}$, where d_{it} is a $K\times 1$ indicator vector with $d_{ijt}=1$ and $d_{ikt}=0$ for $k\neq j$. Denote $Z_{it}=\{X_i, p_{it}\}$, thus

$$L_t(\Theta)=\log\left[\Pr\left(Y_t \middle| Z_{it};\Theta\right)\right]. \tag{11}$$

Note that this likelihood depends on the equilibrium revenue-sharing rule δ_t, which is a nonlinear function of Θ.[11] Hence, we can express the likelihood as follows:

[11] We use successive iteration to solve the game, and provide the algorithm in Appendix B.

$$
\begin{aligned}
& L_t(\Theta) \\
&= \log\left[\Pr\left(Y_t \middle| Z_{it}, \delta_t(\Theta); \Theta\right)\right] \\
&= \log\left[\Pr\left(\lambda_{ijt} \middle| Z_{it}, \delta_t(\Theta); \Theta\right) \cdot \Pr\left(d_{ijt} \middle| \lambda_{ijt}, Z_{it}, \delta_t(\Theta); \Theta\right)\right] \\
&= \log\left[\frac{1}{\sigma_\tau}\phi\left(\hat{\epsilon}^\tau_{ijt}\left(\Theta, \delta_{jt}(\Theta)\right)\right) \cdot \int \Pr\left(d_{ijt} \middle| \lambda_{ijt}, Z_{it}, \left\{\epsilon^\tau_{ikt}\right\}_{k\neq j}, \delta_t(\Theta); \Theta\right) dF\left(\left\{\epsilon^\tau_{ikt}\right\}_{k\neq j}; \Theta\right)\right],
\end{aligned}
\tag{12}
$$

where $\phi(\cdot)$ is the standard normal density, $\hat{\epsilon}^\tau_{ijt}(\cdot)$ is the implied error term in τ_{ijt}, which is solved based on equation (4) and the observed λ_{ijt}.[12] Note that in the second component of this likelihood function we need to integrate over the unobserved realizations of $\left\{\epsilon^\tau_{ikt}\right\}_{k\neq j}$. The realization of ϵ^τ_{ijt}, i.e. $\hat{\epsilon}^\tau_{ijt}$, can be solved from λ_{ijt} and equation (4) as discussed above.

V. RESULTS

In this section, we present the estimation results for both the demand side and the supply side models. We then carry out a profitability analysis and derive welfare implications based on our model estimates.

Consumer Demand Estimates

Before reporting the estimation results, we first describe some empirical definitions in the estimation. The potential market size is defined as the population aged between 20 and 40, who are the most likely to purchase online. We also use review information collected from the largest review website to model the merchant's heterogeneity. Variables include the number of reviews, the average star rating of the reviews, and the variance of the star ratings of the reviews. We only use the reviews prior to the merchant's promotion period when constructing the variables.

[12] A detailed derivation is provided in Appendix A.

We present the estimation results in Table 3. One key parameter in the demand side model is α_{jt}, the platform's ability to generate traffic in the promotion period. The results show that on average, Dianping Tuan has the highest ability, while Meituan has the lowest. Figure 1 shows how this ability changes over time. Interestingly, all of the platforms have the inverted-U shape, which is consistent with the market reactions to daily deals. After becoming popular in a relatively short period of time, the excitement starts to cool down as consumers get used to daily deals. Over time, Dianping is clearly the market leader in terms of generating traffic, which may be because it operates the largest online review platform and thus has built up a large customer base with a strong interest in food and restaurants.

Most of the estimates for the merchant attributes are significant. First, if a merchant operates a chain, it is more likely to generate higher daily deal sales. Intuitively, it provides more flexibility for consumers in redeeming the deal coupon when a merchant has multiple stores in different locations. In terms of reputation, the total number of reviews is a strong predictor of deal popularity. The average review rating is positive but not significant, whereas review variance is positive and significant. High variance could be associated with a niche product, as shown in Sun (2012); this informational aspect could generate higher subsequent demand. This result is consistent with the motivation of participating restaurants. A niche-style restaurant is motivated to participate in daily deals promotions as they are eager to generate awareness and word-of-mouth. Finally, the estimated price coefficient is negative and significant (at the 6% level), indicating that consumers prefer deals that cost less.

Supply Side Estimates

We estimate two sets of parameters on the supply side: the cost function c_i and the future demand impact function τ_{ijt}. We report the estimation results in Table 4.

For the cost structure, our results show that chain restaurants are more efficient than non-chain restaurants, and that high-end restaurants, which are pricy, will have a higher cost structure. We also use user reviews to control for heterogeneity in the cost structure. We believe that in the competitive restaurant industry, operational efficiency directly influences the quality of the food and service, and will thus be reflected in the user reviews. Our results indicate that popular restaurants (with more user reviews) have higher cost ratios, whereas restaurants with good reputations (with higher average user ratings) have advantages in maintaining lower operational costs. Using model estimates, we compute the cost ratio for each merchant in our data. The recovered cost ratios range from 0.43 to 0.80, with a mean value of 0.56. Interviews with some restaurant owners confirm that these numbers are in a reasonable range.

As for τ_{ijt}, the platform's ability to generate future demand for the merchant, our results show clear divergence among platforms. We plot τ_{ijt} for each platform over time, as shown in Figure 2. Whereas most platforms show a decreasing ability to help merchants generate future profits, Dianping Tuan increases its ability over time. In fact, if a merchant promotes through Dianping Tuan, it will generate at least the same level of profit in the future as the profits in the promotion period. This could be because Dianping has the biggest review website, making it easy for consumers to comment on the merchants it features, which in turn might generate greater activity from word-of-mouth.

We also recover the unobserved commission rates from platforms for each daily deal using equilibrium constraints. This is the key challenge in our modeling. The parameter estimate is extremely helpful in understanding the economic value and revenue shares in the daily deals market. We plot the commission rates for each platform for each daily deal over time, as shown in Figure 3. Platforms apparently charge different commission rates when dealing with different merchants. There is a clear U-shape for the commission rates over time. This could reflect a competitive market with few platforms at the beginning, then an increase in the number of entrants, followed by a decrease as fewer firms survive as the market heats up. We also provide descriptive statistics for the commission rates in Table 5. On average, the commission rates across platforms are less than 0.4 (i.e. about 37%), which is significantly lower than Groupon in the US but at the same level as LivingSocial. Comparing the commission rates across platforms, it is evident that they are consistent with the ability of each platform to generate traffic and future demand for merchants.

Although we can only observe the discount rate for realized daily deals, we can recover the discount rates for these deals had they been promoted on platforms other than the one chosen. We plot these discount rates in Figure 5, and report the summary statistics in Table 6. On average, the merchants would give discounts of about 45% in the promotions, and would be more willing to give deeper discounts on Dianping Tuan, i.e. 49% on average, perhaps due to Dianping Tuan's ability to generate greater future profits. Interestingly, the discounts offered by merchants have reduced over time, which is consistent with the increasing commission in the market.

Economic Value of Daily Deals

To achieve our main research objective, we now analyze the economic value of a daily deal for each player: the merchant, the platform, and the consumer. Specifically, we use the model estimates to calculate the profits for the merchant and the revenue for the platform. (We do not have cost information for the platform.) We also calculate the welfare gain for consumers using the equation

$$CW_{ijt} = \frac{M \cdot \ln\left(1+\exp\left(\bar{u}_{ijt}\right)\right)}{|\gamma|}, \tag{13}$$

where $\bar{u}_{ijt} = \alpha_{jt} + \nu_{it} + \gamma \lambda_{ijt} p_{it}$ is the mean utility of buying the daily deals coupon, and γ is the price coefficient. Therefore, consumer welfare is measured in Chinese currency. We report the summary statistics in Table 7.

Several interesting findings emerge from our calculations. As suspected, merchants do lose money immediately after the promotion: the average profit loss during the promotion period is between $493,000 and $1,156,000. This is not surprising given the steep discounts offered by the merchants. However, this loss is completely compensated for by future gains from returning customers, which means that the merchants not only profit from the daily deal promotion, but also earn the largest share of the total surplus. On average, a daily deals promotion generates profits of $74,000 for the merchant and $60,600 for consumers. For the platform, it generates revenue of $22,000, much less than the merchant even before taking out the costs. Therefore, merchants do make money from daily deals, but not in the short term.

The four platforms in this study differ in their ability to generate economic value. Dianping Tuan generates the highest economic value for merchants, consumers, and the platform itself. For example, compared with Lashou, one daily deal in Dianping Tuan can generate more than double the economic value for the merchant, platform, and consumers.

VI. POLICY ANALYSIS

As discussed, the Chinese daily deals market differs from the US market in terms of the level of competition. One consequence of this is the way commission and discount rates are determined. In the US, both Groupon and LivingSocial use fixed commission rates, which are higher than the commissions in the Chinese market. In addition, in most cases these two firms require the merchants to set discount rates at 50%. Some people argue that these fixed rates allow platforms to avoid negotiation costs and deliver consistent services to merchants and consumers. It is also possible that the fixed rates allow the platforms to collude.

In this section, we examine the effect of competition on the economic value generated by daily deals. Specifically, we examine how fixed commission rates or fixed discount rates affect the market equilibrium. In addition, from the regulator's point of view, we evaluate whether the current market practice is close to the social optimal.

Fixed Rate Policy

We first examine the effect of the fixed rate policy and start with the fixed commission rate. Specifically, we assume that all of the platforms charge the same commission rate for all deals. We choose three commission rates: 0.3, 0.4, and 0.5. For each deal in our data, we simulate the market equilibrium, and report them in Table 8.

We compare the results under different fixed commission rates with the status quo. Our earlier analysis shows that the average commission rate is 0.4 in the status quo. Therefore, it is appropriate to first compare a fixed commission rate at 0.4 with the status quo. Our results show that on average, the revenue of the platforms increases by 15%. Consumers are seemly unaffected, although slightly worse off by 0.3%. However, merchants suffer an average loss of 4.5% in profit, most of which is incurred in the promotional period. Comparing the scenario with different commission rates, it is clear that the platforms benefit from a higher commission rate, while it has the opposite effect for the merchants and consumers. However, it seems that the platform is more sensitive to the commission rate than the merchant and the consumer.

Fixed Discount Policy

We then examine the effect of the fixed discount policy. In this simulation, we assume platforms can vary their commission rates, but that the discount rate is fixed to be the same across all platforms. We present the results in Table 9. In general, the results show that not allowing merchants to decide discount rates hurts every party, except when it is fixed at a relatively low discount rate (i.e. a low actual deal price) of 40%. This result is partially driven by an increase in the platform revenue share from 38% (i.e. status-quo) to at least 56% in all simulation cases. Intuitively, not allowing merchants to set optimal discount rates will lower their negotiation power with platforms. In addition, for moderately high discount rates, i.e. 50% or more, demand during the promotional periods is weak, which pushes the platforms to charge a high commission rate. In summary, our results show that the strategic incentive of the merchant is beneficial to social welfare.

Evaluation of Current Practice

We further examine whether the current market practice is close to social optimal. A regulator would like to set up policies to maximize the social welfare. In the daily deals market, it is hard for a regulator to specify the commission rate or discount rate for each deal. Therefore, a realistic approach is to regulate either the platform or the merchant. It would appear to be easier to regulate the platform, given its size and the relatively small number of them.

In this analysis, we assume that each platform has to fix its commission rate, so the regulator's task is to select the optimal commission rate for each platform. We obtain this optimal rate by solving a mathematical programming problem to maximize the sum of platform revenue, merchant profit and consumer welfare. Note that this value is different from the social welfare case because platforms incur operational costs. We assume that the costs do not change with commissions, therefore the solution to our problem also delivers the optimal social welfare. We report the results in Table 10.

It is interesting to note that the optimal social welfare does not significantly deviate from the status quo. In fact, most parties gain only slightly from the policy, which implies that the current market practice is quite close to the social optimal. Interestingly, the social optimal is achieved by lowering the commission rates for the two largest platforms, Dianping Tuan and Meituan. This result seems to suggest that helping the “under-dogs” in this industry helps to increase social welfare overall.

VII. CONCLUSION

Daily deals promotions represent one of the fastest-growing promotion channels for local merchants. However, it is unclear whether merchants benefit from participating in daily deals promotions, thus it is important to quantifying the economic value that they generate. We address this question in this paper, and also discuss how the competition affects the economic value created by daily deals. We develop a structural empirical framework to model the strategic decisions by platforms and merchants in this market. Our model enables us to ascertain the unobserved commission levels and merchant cost levels, and to separate the short- and long-term demand effects generated by the daily deals. We apply our model using comprehensive data from the Chinese market, and focus on a subset of the most valuable merchants. Our findings suggest that merchants do profit from daily deals, although not in the short term.

In fact, merchants grab the biggest piece of the pie from the surplus created by the daily deal, followed by consumers. Platforms obtain much less of the surplus from daily deals. Through simulations, we show how the economic value changes with different price setting scenarios, and so provide a more complete picture of the nature of competition in this market. Our assessment of current practice also confirms that it is fairly optimal from the social planner's point of view.

There are some limitations to our research. To simplify the analysis, we make several assumptions. For example, we focus mainly on competition among platforms for the star merchants in each period. By ignoring the revenues generated by other merchants, we might over-emphasize the competition between the platforms. We also ignore the potential competition between deals by treating each deal as an independent market and modeling the deal sales as a binary choice decision for consumers. In addition, our model identification is based on the assumption that the platforms and merchants are making optimal strategic decisions in setting the commission rates and discount levels. Yet, relaxing either of these assumptions raises great challenges to the model and the estimation strategy. Future research could build on this work and extend the analysis to a more broad-market environment.

This research also does not address other interesting issues in the daily deals industry. For example, a fundamental challenge for the platforms is how to grow their customer bases by strategically attracting certain merchants. How the platforms manage the allocation of resources to deals in different categories represents another interesting question that could have significant implications for product category management. Last but not least, managing customer lifetime value in this daily deals industry is an issue that has not yet been touched on. All of the above questions call for future research in the field.

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APPENDIX A: DERIVATION FOR THE OPTIMAL DISCOUNT RATE

Conditional on choosing platform j, merchant i's profit function is (as given by equation (3)):

$$\pi_{ijt}^{V}\left(\lambda_{ijt}\right)=M\cdot s_{ijt}\cdot\left[\left(1-\delta_{jt}\right)\lambda_{ijt}p_{it}-c_{i}p_{it}\right]+\tau_{ijt}\cdot M\cdot s_{ijt}\cdot p_{it}\left(1-c_{i}\right)+\omega_{ijt}\ .$$

The FOC implies

$$s_{ijt}\left(1-\delta_{jt}\right)+\frac{\partial s_{ijt}}{\partial\lambda_{ijt}}\cdot\left[\left(1-\delta_{jt}\right)\lambda_{ijt}-c_{i}\right]+\tau_{ijt}\cdot\frac{\partial s_{ijt}}{\partial\lambda_{ijt}}\cdot\left(1-c_{i}\right)=0.$$

Substituting $\frac{\partial s_{ijt}}{\partial\lambda_{ijt}}=\gamma p_{it}s_{ijt}\left(1-s_{ijt}\right)$ into the FOC, we have

$$\frac{1-\delta_{ijt}}{1-s_{ijt}}+\gamma p_{it}\left[\left(1-\delta_{jt}\right)\lambda_{ijt}-c_{i}\right]+\gamma p_{it}\tau_{ijt}\left(1-c_{i}\right)=0.$$

Substituting $\frac{1}{1-s_{ijt}}=1+\exp\left(\alpha_{jt}+\nu_{it}+\gamma\lambda_{ijt}p_{it}\right)$ into the above equation, we have

$$\begin{aligned}&\alpha_{jt}+\nu_{it}+\gamma\lambda_{ijt}p_{it}+\exp\left(\alpha_{jt}+\nu_{it}+\gamma\lambda_{ijt}p_{it}\right)\\&=\frac{\gamma p_{it}c_{i}}{1-\delta_{jt}}+\frac{\gamma p_{it}\tau_{ijt}\left(c_{i}-1\right)}{1-\delta_{jt}}+\alpha_{jt}+\nu_{it}-1.\end{aligned}\tag{14}$$

This implies (as given in equation (4))[13]

$$\lambda_{ijt}^{*}=\frac{c_{i}}{1-\delta_{jt}}+\frac{\tau_{ijt}\left(c_{i}-1\right)}{1-\delta_{jt}}-\frac{1}{\gamma p_{it}}-\frac{1}{\gamma p_{it}}W\left(\exp\left\{\frac{\gamma p_{it}c_{i}}{1-\delta_{jt}}+\frac{\tau_{ijt}\gamma p_{it}\left(c_{i}-1\right)}{1-\delta_{jt}}+\alpha_{jt}+\nu_{it}-1\right\}\right),$$

where $W\left(\cdot\right)$ is the Lambert W function.

To derive $\hat{\epsilon}_{ijt}^{\tau}\left(\cdot\right)$, which is used in the estimation, we start from equation (14), which implies

[13] Note that when $x+\exp\left(x\right)=A$, the solution for the variable x is given by $x=A-W\left(\exp\left(A\right)\right)$, where $W\left(\cdot\right)$ is the Lambert W function. Please see http://www.wolframalpha.com/input/?i=x+%2B+exp%28x%29+%3D+A for detail.

$$y_{ijt} = \frac{c_i}{1-\delta_{jt}} + \frac{c_i - 1}{1-\delta_{jt}} \cdot \tau_{ijt}, \tag{15}$$

where

$$y_{ijt} = \lambda_{ijt} + \frac{1}{\gamma p_{it}} + \frac{1}{\gamma p_{it}} \exp\left(\alpha_{jt} + \nu_{it} + \gamma \lambda_{ijt} p_{it}\right).$$

Note that when merchant i is chooses platform j during period t, y_{ijt} is observable (conditional on the demand side estimates). Hence, equation (15) implies

$$\hat{\epsilon}_{ijt}^{\tau} = \frac{y_{ijt}\left(1-\delta_{jt}\right) - c_i}{c_i - 1} - \beta_j^{\tau} \cdot \varphi_{\tau}(t).$$

APPENDIX B: NUMERICAL ALGORITHM FOR THE PRICING GAME

We use successive iterations to compute the equilibrium commission rates given a set of parameters when evaluating the likelihood. Specifically, we first discretize the commission rates from 0 to 1 with step 0.01. Given an initial vector of commission rates, say $\delta^{(0)}$, below is the i^{th} iteration. (Note that there are four platforms in total.)

Step 1: Given $\delta^{(i-1)}$, we define $\delta' = \delta^{(i-1)}$.

Step 2: Given δ'_{-j}, we compute all possible profit for platform j for all discretized commission rates. Suppose the optimal commission rate is δ_j^*, then we update δ' as $\delta'_j = \delta_j^*$.

Step 3: Perform step 1 from $j=1$ to $j=4$, , then update the i^{th} iteration commission rate as $\delta^{(i)} = \delta'$.

Step 4: Repeat step 1 until $\left\|\delta^{(i)} - \delta^{(i-1)}\right\|$ is sufficiently small.

TABLES AND FIGURES

Table 1: Overview of the Competing Platforms

	Lashou	Meituan	Dianping Tuan	Nuomi
Date founded	March 2010	March 2010	June 2010	June 2010
Market share of sales revenue (2012)	8.46%	9.35%	58.99%	14.59%

Table 2: Summary Statistics for the Final Sample

	Min	Q1	Median	Mean	Q3	Max
Deal sales	116	1499	3241	4183	6465	15000
Original price (US$)	2	16	34	36	54	81
Discount	0.20	0.37	0.46	0.49	0.60	0.85
Actual price (US$)	1	9	16	16	22	52
Revenue (US$ 1000)	1.7	20.5	42.9	53.4	76.4	243.3
Number of reviews	2	205	512	779	1067	4326
Average review	2.50	3.45	3.64	3.60	3.80	4.28
Variance of review	0.25	0.65	0.81	0.84	1.00	1.91

Table 3: Demand Side Estimation Results

	Parameter	Estimate	Std. Err	p-value
Lashou	intercept	-10.6605	0.9130	< 0.0001
	period t	5.1129	1.9410	0.0087
	period t^2	-4.8633	2.1879	0.0267
Meituan	intercept	-10.9117	0.9546	< 0.0001
	period t	8.6564	1.5790	< 0.0001
	period t^2	-8.9341	1.6221	< 0.0001
Dianping Tuan	intercept	-9.3996	0.9430	< 0.0001
	period t	2.0068	1.3534	0.1388
	period t^2	-2.6023	1.3134	0.0481
Nuomi	intercept	-10.1764	1.0065	< 0.0001
	period t	5.1589	2.5833	0.0464
	period t^2	-5.3939	2.4685	0.0294
Merchant	is chain	0.2649	0.1537	0.0855
	(log) number of reviews	0.2581	0.0617	< 0.0001
	average review rating	0.2995	0.2298	0.1931
	review variance	0.7140	0.3377	0.0350
	deal price	-1.8004	0.9273	0.0528
Median absolute percentage deviance of sales			51.13%	

Table 4: Supply Side Estimation Results

		Parameter	Estimate	Std Err	p-value
future profit	Lashou	intercept	0.9303	0.0082	< 0.0001
		period t	-0.0521	0.0292	0.0745
		period t^2	-0.0382	0.0464	0.4101
	Meituan	intercept	0.9676	0.0043	< 0.0001
		period t	-0.0163	0.0042	0.0001
		period t^2	-0.0076	0.0096	0.4278
	Dianping Tuan	intercept	1.1119	0.0062	< 0.0001
		period t	0.0904	0.0114	< 0.0001
		period t^2	0.0676	0.0346	0.0507
	Nuomi	intercept	0.8674	0.0038	< 0.0001
		period t	-0.0702	0.0077	< 0.0001
		period t^2	-0.0442	0.0192	0.0215
percentage cost		intercept	-0.0083	0.0040	0.0383
		is chain	-0.1236	0.0046	< 0.0001
		average reported price	0.3313	0.0031	< 0.0001
		(log) number of reviews	0.0731	0.0009	< 0.0001
		average review rating	-0.1193	0.0014	< 0.0001
		review variance	0.0925	0.0043	< 0.0001
σ_τ			0.5921	0.0055	< 0.0001
σ_ω			0.7110	0.0040	< 0.0001
ρ			0.5867	0.0167	< 0.0001
Log-likelihood				-950.7277	

Table 5: Equilibrium Commission Rates (i.e. Platform Profit Share)

	Min	Q1	Median	Mean	Q3	Max
Lashou	0.09	0.26	0.34	0.37	0.44	0.99
Meituan	0.11	0.29	0.35	0.38	0.43	0.99
Dianping Tuan	0.19	0.33	0.38	0.39	0.43	0.99
Nuomi	0.13	0.26	0.32	0.36	0.41	0.99
Matched platform	0.13	0.31	0.37	0.39	0.44	0.99

Table 6: Equilibrium Discount Rate

	Min	Q1	Median	Mean	Q3	Max
Lashou	0.30	0.50	0.58	0.60	0.69	0.85
Meituan	0.29	0.47	0.55	0.58	0.67	0.85
Dianping Tuan	0.25	0.40	0.48	0.51	0.58	0.85
Nuomi	0.33	0.52	0.60	0.62	0.71	0.85
Matched platform	0.28	0.44	0.53	0.55	0.65	0.85

Table 7: Economic Value of Daily Deals

Unit: US$ 1000	Lashou	Meituan	Dianping Tuan	Nuomi	Aggregate
Platform revenue per deal	12.6	22.3	27.1	16.8	22.0
Merchant profit per deal	36.3	76.2	91.9	57.6	74.0
Merchant profit per deal in the promotion period	-49.3	-96.7	-115.6	-70.2	-93.4
Merchant profit per deal in subsequent period	85.5	172.9	207.5	127.9	167.3
Consumer welfare per deal	34.1	61.9	72.5	51.1	60.6

Table 8: The Economic Value of Daily Deals Given Fixed Commission

Unit: US$ 1000	Status Quo	Fixed Commission		
		0.3	0.4	0.5
Platform revenue per deal	22.0	19.7	25.3	30.3
Merchant profit per deal	74.0	77.2	70.7	64.4
Merchant profit per deal in the promotion period	-93.4	-92.4	-96.3	-99.5
Merchant profit per deal in subsequent period	167.3	169.6	167.0	164.0
Consumer welfare per deal	60.6	61.5	60.4	59.3

Table 9: The Economic Value of Daily Deals Given Fixed Discount

Unit: US$ 1000	Status Quo	Fixed Discount			
		0.4	0.5	0.6	0.7
Platform revenue share	38%	60%	56%	57%	61%
Platform revenue per deal	22.0	27.8	20.4	16.0	13.2
Merchant profit per deal	74.0	30.3	27.3	23.0	19.2
Merchant profit per deal in the promotion period	-93.4	-52.6	-27.1	-13.9	-6.9
Merchant profit per deal in subsequent period	167.3	83.0	54.4	36.9	26.1
Consumer welfare per deal	60.6	46.5	35.2	27.6	22.2

Table 10: Comparison between Social Optimal Commission Rates and Status Quo

Unit: US$ 1,000,000	Platform Revenue (Commission Rate)				Merchant	Consumer
	Lashou	Meituan	Dianping Tuan	Nuomi		
Status quo	0.86 (38.87%)	2.48 (36.92%)	5.76 (38.58%)	1.51 (35.64%)	35.66	29.21
Social optimal	0.86 (43%)	2.57 (33%)	5.80 (33%)	1.56 (40%)	35.82	29.48
Increment rate	0.15%	3.79%	0.63%	3.44%	0.47%	0.90%

Figure 1: Platform Time Trend in Demand

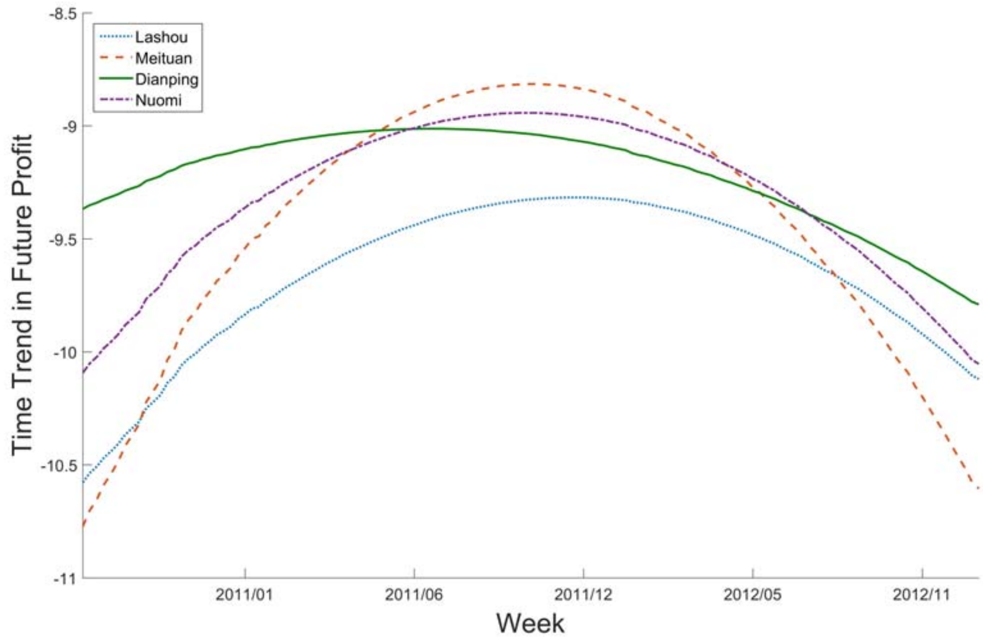

Figure 2: Platform Future Profit Over Time

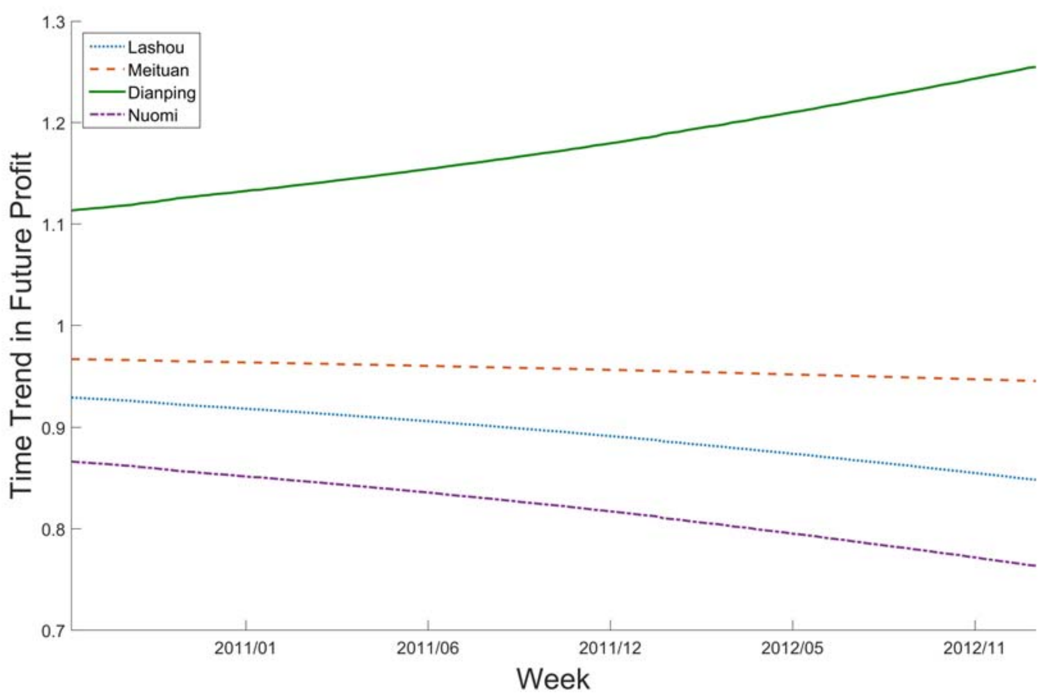

Figure 3: Platform Profit Share Over Time

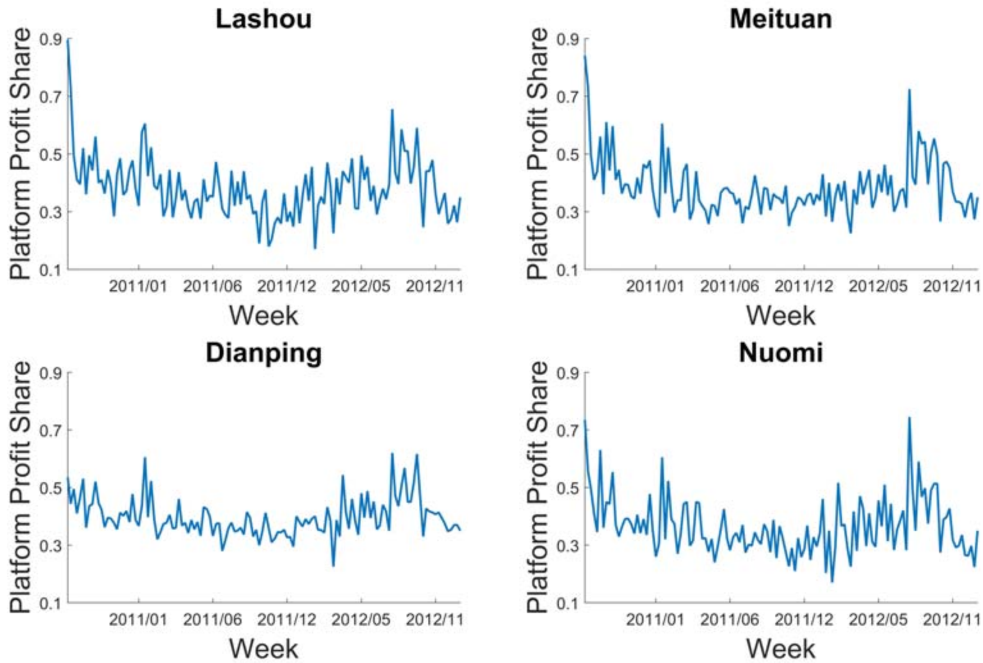

Figure 4: Matched Platform Profit Share Over Time

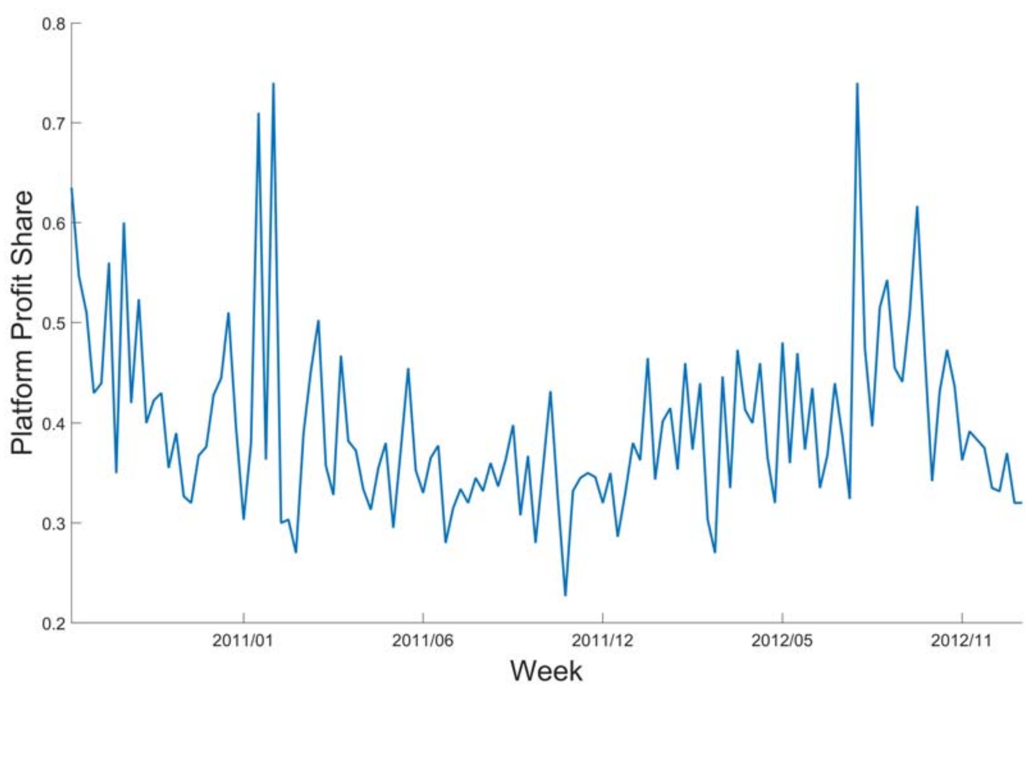

Figure 5: Discount Rate Over Time