Conform or To Be Cast Out: Quantifying the Effect of Platform Endorsement and Consumer Generated Reputation in Online Service Marketplace Demand System

Completed Research Paper

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Abstract

This paper measures the effectiveness of platform endorsement and consumer-generated reputation on sellers' demand in online service marketplace. We apply BLP-style model to understand consumers' heterogeneous sensitivity to platform endorsement and consumer-generated reputation with endogeneity issue handled nicely. In addition, we investigate “conform or to be cast out” policy, which is applied by the platform to enforce sellers to improve one typical platform endorsement as platform refund insurance. Our results provide measurable evidence for that individuals exhibit consistent sensitivity to consumer-generated reputation, whereas perceive most of platform endorsement differently. With regard to the policy, it shows that though “cast out” reduce variety of sellers and thus decreases platform-wise demand and consumer welfare, the negative effect is offset by improvement of platform refund insurance by conforming sellers. Furthermore, we find that the policy shock would lead sellers' further quality escalation, which indirectly benefits platform demand and consumer welfare.

Keywords: demand estimation, service online marketplace, platform endorsement, consumer-generated reputation, consumer surplus

Introduction

The digitalization trend has expanded the product line of online market place from traditional physical products to services. A service marketplace connects businesses with consumers needing anything from a utility fee recharging to a babysitter, infusing immense breadth and tremendous demands to online marketplace. It makes an existing marketplace more transparent, easier to use, be related to popularity.
with online consumers. On the other hand, it is more vulnerable to information asymmetry. As service is intangible and insubstantial, consumers can hardly perceive the quality of service by comparing measurable characteristics with alternatives as accurately as that for physical products. In addition, each service is one-time generated and unique, which incurs variability and inconsistency even by the same provider. Consumers need additional information to infer a more accurate expectation of quality of a service. This makes information provided by the platform crucial for purchase decision making of consumers and thus demands of sellers.

Platform provides three forms of information when categorizing information by identities of its generators. The first form is information solely provided by sellers, such as price, product variety, and membership length. This classic category of information widely exists in not only service online marketplace, but also traditional marketplaces, and is well addressed in past research. The second category is consumer-generated reputation. It is directly created or indirectly derived from evaluations consumers. Typical marketplace verifies the purchases and user reviews, providing the credibility and robustness of consumer generated reputation since no seller can easily manipulate his/her own reviews and ratings or to take down a competitor by malicious tampering. Given its trustworthiness, the reputation mitigates consumers’ uncertainty associated with service by providing a distribution of service quality inferred from past transactions, such as mean of satisfaction, product variability and popularity. Coordination between platform and sellers creates the third type of information as platform endorsement. Shown as unified logo or tags, platform endorsement is widely applied by most of online market place with examples as “trusted sellers” certification, or “On Sale” highlight. Lacking a unified characteristics space for service, platform endorsement provides sellers with a platform-wise standardized characteristics space allowing consumers to evaluate and compare different sellers within a measurable system. The availability of platform endorsement benefits sellers and platform because, different from consumer generated reputation, platform endorsement could be implemented, adjusted and monitored easily by sellers and platform. Sellers can make use of it as strategic tool to increase its competency, whereas platforms can apply it for seller regulation to improve the platform-wise quality to compete with other marketplaces.

Though platform endorsement is widely applied, there is no clear consensus on its effectiveness due to the following challenges. First, unlike consumer-generated reputation which captures an overall measurement of service quality, each platform endorsement only focus on one specific characteristic such as accepting coupons, or having platform refund insurance. It might be favored by a typical party of potential consumers who values that characteristic more than the rest, whereas being negatively perceived since a rational consumer would be able to infer that the cost of platform endorsement is finally converted as markup in the price. Therefore, consumers on the platform might have more heterogeneous tastes for platform endorsement. Second, platform endorsements are potentially endogenous since sellers have the freedom to easily make strategic adjustment of them given unobserved shock of demand. The correlation to be reckoned between unobserved characteristics and platform endorsement constitutes a classic endogeneity problem similarly with that for prices. An examination of their effectiveness will be biased unless the endogeneity issue is well controlled.

The first objective of this paper is to examine the effectiveness of platform endorsement and other information on demand in online service marketplace. Specifically, we apply BLP model to quantify how platform endorsement, consumer generated reputation and seller specific information impact consumers’ willingness to purchase and thus demand for sellers. The BLP model (Berry et al 1995) incorporates random coefficients to allow heterogeneous taste coefficients across consumers and instrument variables to provide unbiased estimates with endogeneity handled nicely. We apply the model with data of a specialized service of recharging prepaid phone remotely. The model allows us to derive numerical marginal effects and elasticities to understand the effectiveness of available information on seller’s perspective. It additionally endows closed-form consumer surplus to address the consumer side impact of the platform endorsement policy and consumer-generated reputation.

The platform announces a “conform or to be cast out” policy to encourage sellers’ registration of one specific type of platform endorsement as “platform refund insurance” during our observation. “Platform refund insurance” program is set to alleviate consumers’ risk aversion to online service by providing a platform-wise insurance that guarantees a full refund of paid amount in credit of platform if consumers dispute a transaction and request a refund. The program benefits consumers by improved after-sale
warranty, however incurs cost for sellers despite insurance premium. To improve the platform-wise service quality, the platform set a “conform or to be cast out” policy to reach a goal of 100% “platform refund” insured sellers in the marketplace. In particular, the platform set week 10 as the start point, and cast out unregistered sellers in the coming 4 weeks. Unregistered sellers who want to continue their business on the platform have to conform by joining the program before being expelled. To our knowledge, there is no prior literature investigating the “conform or to be cast out” policy in online marketplace.  

Our second objective is to analyze the mechanism and effects of the “conform or to be cast out” policy. There are multisided effects in the “conform or to be cast out” policy for different stakeholders. For consumers and the platform, the policy comes with positive side as improved rate of insured sellers and negative one as “casting out” results in decreased variety of sellers. For sellers, the “casting out” rule rewards sellers who decide to stay by squeezed demand from expelled sellers, whereas higher rate of insured sellers mitigate the competitive advantage of sellers adopted the program before the policy. Descriptive demand analysis only identifies compound effect for sellers and platform, suggesting the necessity to use our model to decompose direct effect of each side of the policy and to understand how the policy affects consumer welfare. Furthermore, the exogenous policy changes the market structure, possibly leading to secondary strategic reaction of sellers and establishing new equilibrium. We take the impact of secondary strategic reaction after the policy shock as indirect effect. By using counterfactual simulation based on the estimated BLP model, we examine the direct effects of each sides of the policy, and compare equilibrium before and after the policy to infer potential indirect effect.

Our results show diversified preferences to several platform endorsements and comparably more consistent sensitivities to consumer-generated reputation and seller specific information. With regard to consumer-generated reputation, faster service rate, fewer disputes, fewer required refunds and fulfilled refunds, higher average rating, larger rating volume, more positive evaluations and fewer negative ones increase demand for sellers. Except number of fulfilled refund, all the other dimensions of consumer-generated reputation have relatively small variability parameters, which generate limited impact on demand. However, taste coefficients for platform endorsement distributed dispersedly across consumers except that for short term sale discount, platform refund insurance, VIP store and detailed pictures. The variability of tastes has significant impact on sellers’ demands, resulting in seller-specific marginal effect and substitution effect of platform endorsement. When sellers adjust their platform endorsements such as coupon, short-term VIP seller tag, threshold discount, sampler gift, accepting credit card, and guaranteed return and exchange, a strategy increasing demands for seller A might oppositely affects demand of seller B. In addition, we find platform endorsements such as seasonal short term sale discount mostly generate negative effect on demand, consistent with our conjecture when inferred markup dominates welfare gain of consumers. Consistent with intuition, our analysis shows consumers prefer sellers with lower price, higher level of product variety and longer membership history in the platform. To understand the demand system on the perspective of sellers, we further calculate self and cross market share elasticities of delivery time and that of price, showing the effectiveness to use price and consumer-generated reputation system as tools for demand competition. To measure the impact of policy change on consumers and the platform, we derive consumer surplus for each of the market, and find evidence of welfare loss due to decreased variety and welfare gain due to improved rate of insured sellers.

With regard to the “conform or to be cast out” policy, we decompose the effect of conforming to implement platform refund insurance from that of to be cast out. A marginal analysis with adjustment by one seller and a counterfactual analysis mimicking the market structure change that we observed in data shows that switching to platform refund insurance increase demand of those sellers whereas decrease demand of other sellers who are already in the platform refund insurance program. Coupled with substitution for expelled sellers, the increment for sellers who newly switch is prominent, and the loss of demand of early adopter due to increased competition will be offset fully or partially. From consumers’ perspective, we find that the welfare derived from improved rate of insured sellers overwhelm the loss from less product variety, indicating an overall improvement of performance and competency of the platform. Finally, comparing consumer surplus of a market after the policy change with that of a counterfactual market which have the same level of platform refund insurance registry and same size of sellers but the other characteristics in a market before the policy change are maintained, we find higher consumer surplus for market with after-policy characteristics, indicating sellers’ reaction to the policy leading to further improvement in other characteristics. Despite no analytical solution of the formation of
the new equilibrium, our finding suggests a positive indirect effect of the “conform or to be cast out” policy on consumers and the platform.

**Literature Review**

Our paper builds on and extends the literature that examine how reputation system, platform endorsement, and more generalized website design affect transactional outcomes in the context of online marketplace. Researchers have addressed the effects of specific components of reputation system or the general reputation on different forms of outcomes such as the duration of time to sell products (Ghose 2009), and auction outcome (Bockstedt and Goh 2011) in goods online marketplace. Components of reputation including positive numerical ratings (Ba and Pavlou 2002) and positive textual feedback comments (Pavlou and Dimoka 2006), and other information signals such as diagnostic product descriptions and third-party product assurances (Dimoka et al. 2012), quality of e-image (Gregg and Walczak 2008) are shown to increase price premium. Schlosser et al. (2006) find that website investment signals trustworthiness and increases the intention to purchase of consumers. Wells et al. (2011) discuss how quality of website affects implusiveness of consumption. To our knowledge, one of the closest literatures with respects to our research objective is by Li et al. (2009), demonstrating that revealing quality and credibility indicators such as ratings and money-back guarantee, third-party payment method would encourage bidders to participate in auctions. The closest research with respect to context is by Yoganarasimhan (2013), which uses structural model to measure the effectiveness of reputation system in a typical service marketplace as freelance marketplace. Both Li et al. (2009) and Yoganarasimhan (2013) focus on the setting of online auctions. We differentiate our work with prior literatures by addressing the following aspects: (1) we extend the information signal to platform endorsement, the effectiveness of which is challenging to measure due to its endogeneity; (2) we quantify the effects from all sides of stakeholders’ perspectives, including seller, consumer and platform; (3) we focus on the outcome as demand system to generate more economics insights such as competition; (4) we address the heterogeneity of consumers’ taste to website displayed information.

Our paper also contributes to literature that quantifies consumer welfare in online marketplace. To our knowledge, there are only a few papers focus on measuring consumer welfare. Using field experiment, Bapna et al. (2008) quantify a median surplus of at least $4 per eBay auction extracted by a consumer. Brynjolfsson et al. (2003) estimate consumer welfare of product variety in the context of amazon book store to be between $731 million and $1.03 billion in the year 2000. Ghose and Han (2014) estimate enhanced consumer surplus gained from availability of mobile app to be approximately $33.6 billion annually in the U.S. We extend this stream of literature by measuring consumer welfare in online service marketplace. In addition, coupled with simulation method, our work is the first to measure the direct and indirect utility changes of “conform or to be cast out” policy by calculating compensating variation (CV).

In methodology, our research applies demand estimation method using aggregate data proposed by Berry, Levinsohn, and Pakes (henceforth BLP, 1995). The model shows its superiority in demand estimation by allowing heterogeneity in consumer taste and endogeneity of product characteristics with only aggregate level information of market structure. It also allows estimating consumer welfare given its structure of individual level decision making that maximize latent utility. Its wide applicability allows application across literature in empirical IO, marketing and information system in different formats of industries such as automobile (Berry et al. 1995, 1998 and 1999, Petrin 2002), ready-to-eat cereal (Nevo 2001), movie (David 2001), online hotel booking (Ghose et al 2012) and mobile app usage (Ghose and Han 2014). Our paper extend BLP model to application of online service marketplace which are characterized by high level of information asymmetry and competitiveness. We also extend the applications of BLP model to context of large numbers of players and large space of endogenous actions which are common challenges in literature about online marketplace.

**Data and Descriptive Finding**

Our data are from one of the world’s largest online market place based in China. We focus on online prepaid phone recharging service because this submarket involves identical physical goods as prepaid card and standardized service with concise procedure, which avoids the inflation of error term that captures unobserved characteristics of the service and leaves sellers’ information available online as the main predictor to differentiate demand among sellers. This setup greatly simplifies the model challenges...
and provides us with a good opportunity to investigate the formation of demand with available information online.

The market has enough size and sufficient variety of sellers’ characteristics for us to empirically identify the effectiveness of consumer-generated reputation and platform endorsement. The market is fragmented unevenly. Everyday there are approximately 20,000 active sellers in the platform, with each mega seller occupying as large as 5% of the total market, which is around 70,000 times of that of a 25% quantile small sellers. Note that providing effective information would alleviate information asymmetry in online market due to the intangibility and variability of services. The existence of heterogeneous sellers’ size indicates the effectiveness of information, which avoids typical lemon problem with low quality sellers left. We expect the huge variance of demands to be explained by the reputation system and platform endorsement since it’s the major vein of information based on which consumers make purchase decision.

We collect cross-sectional data for 48 weeks with each week specified as one market. In each week, aggregate level information of seller is collected. Demand is measured as total number of sales for each week. Market share is simply defined as the ratio of demand to total demand of the market, consisting of observed sellers and outside goods providers. Consumer observable pivotal information for making decision is collected regarding to consumer-generated reputation, platform endorsement and other seller generated information. Detailed list of variables are shown in model section. Given that most of consumer-reported information is managed as count data, we take a log transformation of them. All possible platform endorsements during the observation window are collected for each of the seller as dummy variable with 1 indicating seller’s state as with that endorsement. Whenever a seller registers a specific endorsement, the platform will attach a standardized logo to the seller in the page of searching results to highlight the information sellers want to present to consumers. Excluding sellers who have no transaction, we have a sample with 878,665 observations, and 18,306 sellers per week in average.

As we introduced, one of the unique aspect of information our data captures is the “conform or to be cast out” policy. The platform announced the deadline for “conforming” as week 10 in our observation. Our data exhibits that this policy was strictly implemented and significantly remodeled the market structure. In particular, by calculating number of sellers and the percentage of registered sellers, our data shows that the platform started to enforce the expelling policy from week 10, and took four weeks to expel sellers who hadn’t registered. Figure 1 shows more than 20,000 sellers before the implementation of the policy, whereas a sudden reduction of more than 10,000 sellers by the policy. The number of sellers, though fluctuates, increases after the policy in a general trend. The right chart shows that platform start to enforce expelling rule from week 10, and keep on expelling unqualified sellers in the coming four weeks consecutively until the percentage reaches 100% in week 14. Note that percentages after week 14 are not exactly but very close to 100%. It is because those newly entered sellers need additional week(s) to go through the procedural registration with a state shown as unregistered. In addition, the dots in the earlier time periods on right charts shows almost no changes of membership of platform refund insurance before week 10, in support of the absence of forward-looking behavior with regard to registering the program before week 10. Together with the increasing pattern of the number of sellers after week 10, it implies that sellers might have no information about potential policy change in earlier weeks, and thus only have time to strategically react after being expelled when the policy is implemented. The increasing pattern of the number of sellers also indicates that sellers might need to take time to react to the policy, implying off equilibrium in the earlier periods after the policy shock.

**Figure 1 Direct Impact of the “Conform or to be Cast Out” Policy**

![Number of Seller During the Policy](image)

![Percentage of Registered Seller](image)
To understand the impact of the policy change, we further investigate the demand change during these periods. The left chart in Figure 2 exhibits platform-wise weekly demand. Here we find a sudden decrement of sales from week 10, and it lasts for 4 weeks. Comparing this chart with the left chart in Figure 1, we find a positive correlation between number of sellers and total demands, more pronounced during week 19 to week 21 and week 24 to week 27 when moderate falling of number of sellers happened. This is consistent with our conjecture that variability would positively affect the platform-wise demand. Nevertheless, with regard to the scale of demand change when policy happened, the charts presents the decrement of demand around week 10 being not significantly larger than other demand fluctuations, especially when it is compared to the changes of number of sellers. One explanation might be the selection of the policy, as expelled sellers tend to be small sellers who have limited impact on the overall platform demand. Another explanation might be strong substitution to sellers with improved quality by the policy. Even though consumers have less willingness to purchase on the platform due to decreased variety, the loss might be compensated by finding alternative sellers with improved quality with respect to platform refund insurance. If this explanation stands, we would expect an increment of demand for sellers who stay in the market and even more pronounced increment for sellers who newly switched to platform refund policy, because substitution to expelled sellers happens to all staying sellers, and the redistribution favors newly switched sellers more due to improved quality, and early adopters less due to escalated competition. Figure 2 also present average demands for subsets of sellers who are early adopters of the platform refund insurance before week 10 and who are newly switched to the program in week 10 correspondingly. As we expect, the demand after week 10 of early adopters increase but not as significantly as that for newly switched seller, shown as a peak from week 10 to week 15.

**Figure 2 Demand Changes**

An exogenous policy change would result in strategic reaction of sellers until a new equilibrium is established. Figure 2 also present an increment of demand when approaching the new equilibrium. Interestingly, we find that the increment of demand is only concurrent with the market share change of early adopted sellers. In contrast, demand of newly switched sellers, though surged when the policy is introduced, diminishes afterward until it reaches at the level before the introduction of the policy. Note that average market share of early adopters are as large as ten times of that of newly switched sellers. This description suggests in the process of establishing of the new equilibrium, early adopters who are also larger sellers regained their market share from small but newly-switched sellers. Though we don’t examine the formation of competition, the redistribution of demand leads us to suspect indirect effects of the policy stemming from competition after the policy shock.

**Model**

We present a model on data generation process of market share of each seller on the market place. Specifically, we follow McFadden (1973), and more directly Berry, Levinsohn, and Pakes (1995) (BLP) to account for unobserved consumer heterogeneity with a multinomial logistic model. We refer readers to Nevo (2000) for detailed discussion of the methodological advantages of this model.

Suppose we observe sales data of each seller $j = 1, 2, 3, \ldots , J$ in each sub market defined as each time period $m = 1, 2, 3, \ldots , M$. A transaction is defined as a service of recharging prepaid phone which is differentiated with regard to service by seller such as delivery time and fulfillment rate. Consumers $i = 1, 2, 3, \ldots , I$ can not have perfect information of quality of service; therefore rely on information provided by the platform to infer expected quality to help making decision of choosing seller. The conditional indirect utility that consumer $i$ purchases service from seller $j$ at market $m$ is assumed to be of the form
\[ u_{jm} = \beta_j X_{jm} + \xi_{jm} + \epsilon_{jm}. \] (1)

The first component in our utility function is \( X_{jm} \), a vector capturing multi-dimensional observable characteristics of seller \( j \). Assuming that consumers would access information for the whole potential sellers when they are looking forward a service, consumers would receive signals from \( X_{jm} \) to form expectations of service quality by distinct sellers in a given market. There are three categories of information: past consumers generated reputation, platform endorsement and other seller specific information. We include all numerically measurable variables relevant to sellers’ reputation generated by past consumers as following: (a) \( x_{1jm} \) cumulative average delivery time; (b) \( x_{2jm} \) log of cumulative count of disputes; (c) \( x_{3jm} \) log of cumulative count of required refund; (d) \( x_{4jm} \) merchandise average rating generated by consumer with the scale of 1 to 5; (e) \( x_{5jm} \) log of cumulative volume of ratings; (f) \( x_{6jm} \) log of cumulative count of refunded transactions; (g) \( x_{7jm} \) log of cumulative number of past transactions with positive evaluations; (h) \( x_{8jm} \) log of cumulative number of past transactions with negative evaluations. We include all possible combination of platform endorsement for each seller such as: (i) \( x_{9jm} \) dummy for accepting coupon tag; (j) \( x_{10jm} \) dummy for short-term VIP seller tag; (k) \( x_{11jm} \) dummy for threshold discount tag; (l) \( x_{12jm} \) dummy for giving sampler gift tag; (m) \( x_{13jm} \) dummy for seasonal short term sale discount; (n) \( x_{14jm} \) dummy for VIP store tag; (o) \( x_{15jm} \) dummy for accepting credit card; (p) \( x_{16jm} \) dummy for detailed picture of product; (q) \( x_{17jm} \) dummy for platform refund insurance for potential consumers; (r) \( x_{18jm} \) dummy for guaranteed return and exchange within one week. The last type of information is purely determined by sellers. It consists of (s) \( x_{19jm} \) log of number of distinctive type of product, which are used to capture variety and scope of products for a specific seller; (t) \( x_{20jm} \) log of number of days since registered on the platform, capturing duration of membership on the platform; (u) \( x_{21jm} \) average price of the product.

Other than different characteristics of sellers, we incorporate further consumer heterogeneity by introducing heterogeneous tastes towards different characteristics. We model taste parameters \( \beta \) as random coefficients to allow different individuals have distinct preference towards a specific characteristic. Specifically, we follow BLP to model \( \beta \) following a multivariate normal distribution as following,

\[ \beta_j \sim \beta + \sum \nu_j \] (2)

\[ \nu_j \sim MVN(0, I). \] (3)

\( \beta \) is a 21 by 1 vector of mean parameters that are common across different individuals, capturing the mean sensitivities towards different characteristics, whereas \( \sum \nu_j \) captures individual level heterogeneity in their preference towards characteristics. Following BLP method, we model \( \nu_j \) following multivariate normal distribution with mean of zero and standard diagonal variance. Given that individuals might have different level of variability towards different characteristics, we use \( \sum \) to rescale the variance of taste coefficients.

Consumers might capture additional information of sellers which is unobserved by econometrician, e.g. offline reputation. We therefore denote \( \xi_{jm} \) as information about seller \( j \) in market \( m \) observed by consumers but not by us. It is market and product specific, and is common to all individual consumers. Consumers prefer a product with higher \( \xi_{jm} \) since it provides more expected utility.

Finally, consumers also have individual and choice specific unobserved information which is different across distinct consumers. We represent it as \( \epsilon_{jm} \), and assume it to be independent and identically distributed across both products and consumers following type-I extreme distribution. After rearrange the
utility function in a more hierarchical way and define seller level mean utility as \( \delta_{jm} = \beta X_{jm} + \xi_{jm} \), we have a suppressed format of utility as following
\[
    u_{jm} = \delta_{jm} + \sum v_j X_{jm} + \varepsilon_{jm}. \tag{4}
\]
We accomplish the specification of the demand system by introducing utility of outside goods: individuals might decide not to purchase the service from our online marketplace. They might purchase similar service from other online business or offline channel. We model the conditional indirect utility from the outside goods as
\[
    u_{jm} = c_0 + \nu_0 \sigma_0 + \varepsilon_{jm}, \tag{5}
\]
where \( c_0 \) captures mean utility of outside goods, and \( \nu_0 \sigma_0 \) is an individual specific component reflecting heterogeneity in preference to take outside goods. We model \( \nu_0 \) as a standard normal distribution \( N(0, 1) \) independently and \( \sigma_0 \) as a scaler parameter to be estimated. Another representation is to take \( c_0 \) as one more dimension of \( \beta \) with a constant covariate, and take \( \nu_0 \) as an additional dimension of \( \varepsilon_{jm} \), which lead the mean coefficient \( \beta \) to be a 22 by 1 vector, the taste heterogeneity distribution to follow 22-variates \( \text{MVN}(0, I) \), and \( \sigma_0 \) as an additional dimension of \( \Sigma \). \( \varepsilon_{jm} \) is “love of variety” individual level random error term following type-I extreme distribution.

Given the property of type-I extreme distribution in conditional multinomial discrete choice model, we would have a closed form probability that consumer \( i \) would purchase product \( j \) in market \( m \) according to
\[
    \Pr_m(j | X, i) = \frac{\exp(\delta_{jm} + \sum v_j X_{jm})}{\exp(c_0 + \nu_0 \sigma_0) + \sum \exp(\delta_{jm} + \sum v_j X_{jm})}. \tag{6}
\]
Market shares are obtained by aggregating over population of potential consumers. Given that \( \nu_0 \) is distributed as 22 variates \( \text{MVN}(0, I) \), we use \( P(\nu_0) \) to denote a population distribution function of individual heterogeneity to taste coefficients. By taking integration over \( \nu_0 \), we can further derive market share \( s_{jm}(\delta_{jm}, \theta) \) of seller \( j \) in market \( m \) as following,
\[
    s_{jm}(\delta_{jm}, \theta) = \int \Pr_m(j | X, i) d(P(\nu_0)) = \int \frac{\exp(\delta_{jm} + \sum v_j X_{jm})}{\exp(c_0 + \nu_0 \sigma_0) + \sum \exp(\delta_{jm} + \sum v_j X_{jm})} d(P(\nu_0)), \tag{7}
\]
where \( \theta = \{\beta, \Sigma\} \).

**Estimation**

**Identification**

We resemble the generalized method of moment (GMM) approach proposed by Berry et al (1991). The GMM-based BLP method essentially estimates the parameter to rationalize two sets of moment conditions. The first one equates market share predictions to the observed market share from our data, which is shown as following,
\[
    s_{jm}(\delta_{jm}, \theta) - s_{jm} = 0 \text{ for } j = 1, \ldots, J, \text{ and } m = 1, \ldots, M. \tag{9}
\]
Berry (1994) shows the existence and uniqueness of \( \delta_{jm} \) that guarantee this moment under mild regularity conditions on the distribution of consumer tastes.
The second moment condition is about market level disturbance. It requires those unobserved market level disturbance \( \xi_{jm} \) to be uncorrelated with observed exogenous variables and instrument variables denoted as \( Z \) shown as

\[
E(\xi_{jm} | Z) = 0 \quad \text{for} \quad j = 1, 2, \ldots, J, \text{and} \quad m = 1, 2, \ldots, M. \tag{10}
\]

The first moment guarantees a mapping between \( \Sigma \) and \( \delta_{jm} \). Given one specific \( \delta_{jm} \) and second moment condition above, we could take \( \beta \) as coefficients in linear regression with \( \delta_{jm} \) as dependent variables and \( \xi_{jm} \) as random shock. This analogy indicates identifiability of \( \beta \) given \( \delta_{jm} \). With both conditions combined, we would have unique optimal extremum point identifying both \( \Sigma \) and \( \beta \).

**Instrument Variables**

Similar with many empirical works of online market place, our model is faced with critical challenge of endogeneity. Endogeneity biases arise when firms are allowed to choose or adjust product characteristics \( X \) given other information which is unobserved to econometrician \( \xi_{jm} \). Traditional demand estimation literature (Berry et al 1995, Petrin 2002) assumes price as the only adjustable strategic action by sellers in short run, whereas takes other characteristics as exogenous. Nevertheless, in case of online service marketplace, a much larger action space is adjusted on a relatively high frequency basis, which is unable to instrument itself. In fact, only past consumer generated reputation and sellers’ duration of membership are exempt from simultaneity issue given new consumers would only have access to reputation system updated to time \( m-1 \), which is earlier than the arrival of unobserved demand shock at \( m \). Seller can adjust their platform endorsement characteristics simply by registering corresponding service from platform manager, implying that platform endorsement characteristics could be outcomes of strategic actions given market and product demand shock \( \xi_{jm} \). Similar argument could be applied to price and variety of products, which are classic assumption for supply and demand system. In a more econometric interpretation, \( \{x_{0jm}, x_{10jm}, x_{11jm}, x_{12jm}, x_{13jm}, x_{14jm}, x_{15jm}, x_{16jm}, x_{17jm}, x_{18jm}, x_{19jm}, x_{21jm}\} \) are highly possible to be correlated with \( \xi_{jm} \), which leads harmful biasness towards our estimates.

We follow BLP and Berry (1994) to apply measures of isolation in product space as instrument variables. The idea is similar to cross-validation which measures how different a product characteristic is from the market average characteristics. BLP shows that it is solid to use these instruments when price is the only endogenous variable and other characteristics could be taken as fixed and exogenous, which is less demanding than our setting in which other characteristics might also be correlated with seller specific shock. However, similar justification can be easily extended to our context. Note that our model focus on a highly fragmented market, different from BLP models focusing on a duopoly or oligopoly cases. It implies that each seller’s unobserved characteristics can hardly have impact or reshape market average characteristics. In other words, even though seller specific unobserved characteristic is likely to be correlated with seller specific characteristics or that of a competing seller, it is unlikely to be correlated with market average characteristics. Therefore, we can still use BLP style instrument in our estimation.

One limitation of BLP style instrument is limited variation for certain variables, we therefore supplement it with the second set of instrument variables as Villas-Boas-Winer-style instrument variables (Villas-Boas and Winner 1999), which uses lagged characteristics as instrument variables. Recall that we define each market as a market in certain time period. Villas-Boas-Winer-style IVs in our example is indeed a special form of Hausman style instrument variables (Hausman 1997) if we take characteristics of a specific seller in other time as a special case of the characteristics of similar seller in the other markets. The intuition behind is that a demand shock in time \( t \) might result in strategic adjustment of characteristics in time \( t \), however, it will not result in adjustment of characteristic in time \( t - 1 \) due to the reversed order. Given characteristics of a seller across time periods are correlated due to the continuity of strategic behavior and similar cost structure, lagged characteristics are valid instruments.

Lastly, we include lagged cumulative sales during time \( m-1 \) for each seller as instrument. It is information visible to consumer, but being dropped from our main model due to very high collinearity.
with other characteristics variables measuring cumulative counts and difficulty to normalize other variables with regard to lagged cumulative sales due to very high portion of sellers have zero sales up to last period. However, it is uncorrelated with seller specific demand shock but highly correlated with the strategic action variables including platform endorsement as well as pricing of sellers. Therefore, we include it as the third type of instrument variables.

**Estimation Result**

**Parameter Estimates and Marginal Effects**

In Table 2, we present mean coefficient and variability coefficient for each characteristics with their standard errors.

**Table 2 Estimation Results**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Base Coefficients</th>
<th>Variability Coefficients</th>
<th>Marginal Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mega Seller</td>
</tr>
<tr>
<td>Delivery time</td>
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<td>0.88*</td>
<td>-4.26%</td>
</tr>
<tr>
<td>#Dispute</td>
<td>-0.11***</td>
<td>0.22***</td>
<td>-0.32%</td>
</tr>
<tr>
<td>#Refund RQST</td>
<td>-0.11*</td>
<td>0.16***</td>
<td>-0.05%</td>
</tr>
<tr>
<td>Avg rating</td>
<td>0.50**</td>
<td>0.06***</td>
<td>1.86%</td>
</tr>
<tr>
<td>Rating volume</td>
<td>0.97***</td>
<td>0.11***</td>
<td>3.72%</td>
</tr>
<tr>
<td>#Refund</td>
<td>-0.19***</td>
<td>0.56***</td>
<td>2.28%</td>
</tr>
<tr>
<td>#Positive EVAL</td>
<td>0.69***</td>
<td>0.03*</td>
<td>2.64%</td>
</tr>
<tr>
<td>#Neg EVAL</td>
<td>-0.09***</td>
<td>0.08***</td>
<td>-0.32%</td>
</tr>
<tr>
<td>Coupon</td>
<td>0.02</td>
<td>1.06</td>
<td>-5.16%</td>
</tr>
<tr>
<td>Short-term VIP</td>
<td>-0.33**</td>
<td>1.01***</td>
<td>2.17%</td>
</tr>
<tr>
<td>TD</td>
<td>-0.11</td>
<td>1.03***</td>
<td>11.66%</td>
</tr>
<tr>
<td>Sampler gifts</td>
<td>-0.70***</td>
<td>1.02***</td>
<td>-22.39%</td>
</tr>
<tr>
<td>Short term sale</td>
<td>-1.66***</td>
<td>0.85***</td>
<td>-55.04%</td>
</tr>
<tr>
<td>VIP store</td>
<td>0.23*</td>
<td>0.86***</td>
<td>8.81%</td>
</tr>
<tr>
<td>Credit card</td>
<td>-0.17*</td>
<td>0.95***</td>
<td>8.24%</td>
</tr>
<tr>
<td>Detailed picture</td>
<td>0.22</td>
<td>1.03**</td>
<td>20.39%</td>
</tr>
<tr>
<td>PRI</td>
<td>0.64***</td>
<td>0.23***</td>
<td>21.12%</td>
</tr>
<tr>
<td>SGR</td>
<td>-0.44***</td>
<td>0.23***</td>
<td>-35.80%</td>
</tr>
<tr>
<td>Product variety</td>
<td>0.12**</td>
<td>0.01***</td>
<td>0.44%</td>
</tr>
<tr>
<td>Duration</td>
<td>0.49**</td>
<td>0.10*</td>
<td>1.55%</td>
</tr>
<tr>
<td>Price</td>
<td>-3.04**</td>
<td>0.01***</td>
<td>-10.84%</td>
</tr>
<tr>
<td>Outside goods</td>
<td>2.35</td>
<td>0.03*</td>
<td>-</td>
</tr>
</tbody>
</table>

*Z statistics > 1   **Z statistics > 2   ***Z statistics > 3

To interpret the estimated model, one thing worth noting is the good property of random coefficient logit model that allows distinct sellers have different marginal effects for a specific variable. It incorporates more degree of freedom of the model to fit in, and thus leads to more realistic interpretation of the results. However, it incurs confusion when the sign of mean parameters are not consistent with the sign of marginal effect because of nonlinearity of multinomial logit transformation and the integration over random coefficients. Note that linear models would always have marginal effect be consistent with mean effect because the integration over random coefficients would always be equals to mean effect. A nonlinear transformation of random coefficients would make the marginal effect deviate from that of model with mean coefficient only. In other words, the variability parameters infuse additional effect than that from mean parameters when nonlinear transformation is imposed. When the sign of variability effect is opposite to that of the mean effect, marginal effect will be opposite to the mean effect if variability effect shows more strength. Therefore, researchers need to be extreme meticulous to interpret coefficient with large variability parameter.

We present marginal effect of each variable in addition to estimate of mean parameter and that of variability parameter to avoid any potentially misleading results. Since marginal effect of each characteristic is seller and market specific, we calculate marginal effect of several representative sellers.
including a mega seller who have market share over 5%, a median seller and a 25% quantile (small) seller in market $m = 1$ (we name them as representative sellers interchangeably). The margin we use is 0.1 increment for average rating and log(110%) increment for log transformed variable in Euclidean distance. Since dummy variables are not differentiable, we present marginal effects by doing what-if analysis to show the difference between effect of data-observed choice and that of alternative choice. Exhibiting marginal effect, we provide a more direct and explicit understanding of the impact of each characteristic on market share, compared with interpreting the value of coefficients only. We summarize the numerical results as percentage of marginal demand in relative to current demand for representative sellers in the last three columns of Table 2.

Our results show the effectiveness of consumer generated reputation. Most coefficients are significant with the expected signs. All else being equal, consumers are qualitatively more inclined to consume at sellers with faster service speed, fewer disputes, fewer required refunds and fulfilled refunds, higher average rating, larger rating volume, more positive evaluations and fewer negative ones. Most of the marginal effects of consumer generated reputation are consistent with sign of mean parameters given that variabilities are mostly moderate to small, with the exception of cumulative fulfilled refund count (log), whose variability parameter ($0.56$) is at least three times larger than mean parameter ($-0.19$), implying very fat tails of coefficient distribution and thus very heterogeneous tastes towards this variable. One possible explanation for high variability is that refund count on one hand negatively impacts on consumers’ utility by representing risk of extra cost associated with a failed transaction, on the other hand signals its positive side as implying sellers’ willingness to undertake responsibility.

Platform endorsement, on the other hand, shows very heterogeneous tastes of consumers except platform refund insurance, in support of our conjecture that rational individuals would be able to perceive the cost of endorsements as markup in the price, and the benefits of endorsement would only be applied to a subset of targeting consumers. Recalling that the sign of mean parameters might be inconsistent with that of marginal effects when variability is large, the interpretation of mean parameters might not be as meaningful as marginal effect. Our calculation suggests that the effect of variability parameters for platform endorsement could be large to contrasting the sign of marginal effect with that of mean parameters. Specifically, the endorsement with lower variability parameter have sign of marginal effect be consistent with that of mean parameter. Surprisingly, short term sales discount tag is shown as negative for demands with -55.04%, -52.07% and -71.35% marginal effects for representative sellers and negative mean parameter. The reason might be that sales tag is no longer attractive given price is transparent. On the other hand, platform endorsement with higher variability parameters exhibit marginal effects with opposite sign to mean parameter for part or all of the sellers. In particular, threshold discount tag, though shown as negative in mean parameter, increase demand by 11.66%, 37.36% and 52.90% for representative sellers. Similarly, accepting credit card tag generates 8.24%, 11.46% and 14.06% additional demand, in contrast with its sign of mean parameter. Our results also show monotony of marginal effect with regard to size of sellers, indicating the possibility that only one end of sellers in size dimension exhibit contrasting marginal effect, e.g. coupon tag, though decrease demand by 5.16% for mega seller, increases demand by 70.47% and 96.79% for median seller and small seller; short-term VIP seller tag, though increase sales of mega seller by 2.17%, decrease that of median and small sellers by 4.46% and 6.15% respectively; sampler gifts tag shows positive effect on demand by 16.97% for median seller and 25.40% for small seller, on the other hand, lowers demand by 22.39% for mega seller; Seller guaranteed return and exchange tag fosters demand of median and small seller by 9.45% and 10.93% respectively, whereas decrease mega sellers’ demand by 35.80% correspondingly. Those findings suggest platform endorsement good for small and median sellers might be harmful to mega seller, and vice versa. It also indicates the potentially incorrect qualitative interpretation of estimation results if researchers only focus on the sign of mean parameters, addressing importance of incorporating random coefficients in demand estimation.

We find expected effect of other seller specific characteristics. With moderate variability parameter estimate, sign of mean parameters exhibits consistency with that of marginal effects. Product variety positively increase demand by 0.44%, 0.82% and 1.12% for representative sellers. 10% longer duration of membership also increase sales by 1.55%, 2.86% and 3.98% for representative sellers, implying consumers’ preference of sellers with longer transactional history. As expected, 10% increase of price lowers demand by 10.84%, 18.41% and 25.17% for mega, median and small sellers respectively.
**Substitution Effects**

A strategic characteristic adjustment by seller would not only have impact on that seller himself, but also exhibits externalities by affecting demand of competitors. To understand the externalities in online service marketplace, we calculate self and cross elasticity of demand for continuous variables. Given the large number of sellers and high dimensional characteristics, we only apply the calculation on delivery time and price for selected representative sellers as 0.25 quantile (small) seller, median seller, 0.75 quantile (large) seller and mega seller in market \( m = 1 \) according to

\[
\eta_{jmn} = \frac{\partial x_{jm} x_{km}}{\partial x_{jm} s_{jm}} = \begin{cases} 
\frac{x_{jm}}{s_{jm}} \beta_j s_{jm} (1 - s_{jm}) d(P(v)) & \text{if } j = k \\
\frac{x_{jm}}{s_{jm}} \beta_j s_{jm} s_{jm} d(P(v)) & \text{otherwise}
\end{cases}, \quad (13)
\]

where \( \eta_{jmn} \) measures the responsiveness of the demand of seller \( j \) with change of characteristics of seller \( k \). \( s_{jm} \) is the market share of seller \( j \) in market \( m \). \( x_{jm} \) is the changing variable of seller \( k \) in the same market. \( \beta_j \) is consumer specific parameter associated with the changing variable. \( s_{jm} (s_{km}) \) is succinct representations of individual specific willingness to purchase as \( \Pr_{m}(j | X, i) \) ( \( \Pr_{m}(k | X, i) \) ) shown in equation (7). For explicit interpretation, we additionally calculate counterfactual marginal effects of representative sellers to measure the changes of market share were one seller to make strategic adjustment. In Table 3 and Table 4, we take the characteristics of seller in the head of each row as changing variables, and calculate marginal effects and elasticity to measure responsiveness of demand of the seller in the head of each column.

Delivery time was investigated firstly because of its strongest marginal impact among consumer generated reputation. Coupled with negative self-elasticity, positive cross elasticity implies that decreasing delivery time would allow seller to substitute demand squeezed from market shares of other sellers. When lowering delivery time by 10%, demand of seller increases proportionally to self-elasticity and size of a seller, whereas demand of competitor drops proportionally to its own size and the increment of changing sellers’ demand. Therefore, the larger the size of a changing seller is, the stronger externalities it will exhibits; the larger the size of responding seller is, the stronger impact it will receive.

**Table 3 Delivery Time (log) Substitution Pattern**

<table>
<thead>
<tr>
<th>Marginal Market Share with 10% Decrease in Delivery Time</th>
<th>Delivery Time Elasticity of Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mega</strong></td>
<td><strong>L</strong></td>
</tr>
<tr>
<td>1.85E-3</td>
<td>-4.94E-11</td>
</tr>
<tr>
<td>-5.04E-11</td>
<td>8.74E-07</td>
</tr>
<tr>
<td>-1.86E-11</td>
<td>3.08E-07</td>
</tr>
<tr>
<td>-7.77E-12</td>
<td>-1.05E-13</td>
</tr>
</tbody>
</table>

As a classic question in economic study, we measure price elasticity of demand and the changes of demand when changing seller drops its price. Consistent with the property of a competitive market, we find large and positive price self-elasticity of demand and negative cross-elasticity, suggesting price war as an effective strategy to squeeze demand from competitors. By examining the scale of market shares changes when changing seller provide 10% price discount, our results show that compared with smaller sellers, larger seller would occupy more additional market share and thus result in more loss of competitors when it is the changing seller, whereas loss more too when competitor(s) play the role as changing seller.

**Table 4 Price Substitution Pattern**

<table>
<thead>
<tr>
<th>Marginal Market Share with 10% Decrease in Price</th>
<th>Price Elasticity of Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mega</strong></td>
<td><strong>L</strong></td>
</tr>
<tr>
<td>4.91E-3</td>
<td>-1.68E-10</td>
</tr>
<tr>
<td>-1.72E-10</td>
<td>1.98E-06</td>
</tr>
</tbody>
</table>
### Consumer Welfare Analysis

Our model allows us to analyze the impact of changes of market structure on consumer side by providing a closed form solution for consumer surplus. Therefore, we calculate the individual consumer surplus across different time periods to examine how compound market structure change affects consumers. Following McFadden (1981), we calculate the average individual level consumer surplus in random coefficient logit model according to

$$CW_m = \int \frac{\ln(\sum_{j=1}^{J_m} \exp(u_{ijm}))}{-\beta_{2i}} d(P(\nu_i)), \quad (14)$$

where $u_{ijm}$ is the individual specific indirect utility function shown in equation (4) and (5), $J_m$ is the number of sellers available in market $m$, and $\beta_{2i}$ is the individual specific coefficient for price which equal to mean parameter $\beta_{2i}$ plus individual specific deviation from the mean parameter $\Sigma_{2i} \nu_i$. By dividing indirect utility by marginal effects of income $\beta_{2i}$, $CW_m$ estimates the consumer welfare in monetary unit. Taking a difference between $CW_m$ in market $m$ and $CW_0$ as consumer welfare in a benchmark market structure would lead to compensating variation (CV) and equivalent variation (EV). Therefore, comparing $CW_m$ allow us to understand whether consumers are better off given a specific market structure.

We present the consumer welfare along with time (markets) in Figure 4, which shows that an average consumer would gain 0.5 to 2 (RMB) from the availability of the online service marketplace. As time goes on, consumers are shown to be better off with an increasing trend of consumer surplus. Recall that the platform start “conform or to be cast out” policy on week 10, our result is consist with past literature showing increased consumer welfare with higher level of product variety (Brynjolfsson et al. 2003, Ghose et al. 2006) by observing a decreasing pattern of consumer surplus when sellers are expelled after week 10. Nevertheless, consumer surplus rebounds as the market structure moves to a new equilibrium after the exogenous shock.

![Figure 4 Average Consumer Welfare](image)

Note that the total number of sellers rebounds too after the policy but is still much less than that before the policy. Researchers might draw a careless conclusion as platform refund insurance plays a more pronounced role than seller variety with respect to consumer welfare. However, such conclusion is hasty since it potentially overvalued the direct effect of policy change and overlooks the indirect effect generated from endogenous reactions of sellers. One possible indirect effect is escalation of competition. One typical way to analyze sellers’ strategic behavior after a policy shock is to derive a theoretical optimal action assuming sellers are all profit maximizer. This approach is contradicting with our observation as sellers are not rational enough to optimally behave immediately, and is theoretically impossible to solve with high dimension of action space and larger number of players in our context. We therefore take an alternative approach as using counterfactual simulation to approximately decompose the overall effect of
the policy on consumer welfare into direct effects and potential indirect effect to deepen our understanding of the “conform or to be cast out” policy.

**Policy Simulation**

**Direct Effect of “Conform”**

We firstly investigate the marginal direct effect of platform refund insurance. In particular, we conduct counterfactual simulation to investigate the impact on sellers and calculate consumer welfare to provide insights on the perspective of platform and consumers. To understand the marginal self-effect and externalities, the counterfactual analysis simulates the market shares of all sellers when one specific seller switches its state of platform refund insurance and calculates marginal effect by differencing market shares between the original market and the simulated one shown in Table 5, where head of each role is the changing seller. Due to limited space, we report effects on representative sellers including mega seller, 0.75-quantile (large) seller, median seller and 0.25-quantile (small) seller, and the overall externalities denoted as “All Others” column. Table 5 exhibits that the platform refund insurance on one hand increase demand of seller who adopts it, on the other hand lower demand of other unchanged sellers. With respect to the scale, the larger the size of the seller is, the more additional demand it will gain and the stronger negative externalities it will impose if adopting this endorsement by itself, and the stronger negative impact it will receive if other seller(s) is the changing one.

We further calculate consumer welfare by taking the difference of consumer surplus between original setup and counterfactual setup shown as last column in Table 5. As we expected, our result shows that sellers’ adoption of platform refund insurance will benefit consumers, and adoption by a larger seller would generate higher level of consumer welfare.

**Table 5 Direct Effect of Platform Refund Insurance**

<table>
<thead>
<tr>
<th>Demand Marginal Effect on Seller</th>
<th>Consumer Welfare</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mega</td>
<td>CV(EV)</td>
</tr>
<tr>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td>-2.19E-10</td>
<td></td>
</tr>
<tr>
<td>-7.77E-11</td>
<td></td>
</tr>
<tr>
<td>-2.60E-11</td>
<td></td>
</tr>
<tr>
<td>0.001</td>
<td>0.01</td>
</tr>
<tr>
<td>L</td>
<td></td>
</tr>
<tr>
<td>-3.74E-10</td>
<td></td>
</tr>
<tr>
<td>6.09E-06</td>
<td></td>
</tr>
<tr>
<td>-1.84E-11</td>
<td></td>
</tr>
<tr>
<td>-5.12E-12</td>
<td></td>
</tr>
<tr>
<td>-2.26E-06</td>
<td>7.03E-07</td>
</tr>
<tr>
<td>M</td>
<td></td>
</tr>
<tr>
<td>-1.34E-10</td>
<td></td>
</tr>
<tr>
<td>-1.84E-11</td>
<td></td>
</tr>
<tr>
<td>2.13E-06</td>
<td></td>
</tr>
<tr>
<td>-1.80E-12</td>
<td></td>
</tr>
<tr>
<td>-7.78E-07</td>
<td>7.03E-07</td>
</tr>
<tr>
<td>S</td>
<td></td>
</tr>
<tr>
<td>-2.29E-11</td>
<td></td>
</tr>
<tr>
<td>-2.40E-12</td>
<td></td>
</tr>
<tr>
<td>-8.43E-13</td>
<td></td>
</tr>
<tr>
<td>2.29E-11</td>
<td></td>
</tr>
<tr>
<td>-1.04E-07</td>
<td>9.31E-08</td>
</tr>
<tr>
<td>All</td>
<td></td>
</tr>
<tr>
<td>-2.68%</td>
<td></td>
</tr>
<tr>
<td>9.38</td>
<td>0.04</td>
</tr>
<tr>
<td>Already Registered</td>
<td></td>
</tr>
<tr>
<td>Newly Registered</td>
<td></td>
</tr>
</tbody>
</table>

To understand the overall direct impact when all sellers are required to register, we further simulate a case with all sellers registered shown as the last two rows in Table 5. Our results show that when all sellers are registered, sellers who had been already registered would be worse off due to increased competition, and sellers who are newly registered would be better off given its improved competency. Overall, the policy creates 6.70% additional demand for the platform as a net of 2.68% loss of demand from sellers who have registered and 9.38% increment from newly registered sellers. Given that the quality of every seller’s service is improved with platform refund insurance, consumers are supposed to be better off, which is validated by 0.0408 increment of consumer surplus.

**Direct Effect of the “Conform or To Be Cast Out” Policy and Potential Indirect Effect**

In this section we investigate the overall direct effect when sellers are not allowed to make any strategic adjustment, and further derive indirect effect when sellers’ reactions are considered. Specifically, we use market 1 and market 48 to represent markets before and after the policy correspondingly because these two markets are the farthest markets to the policy change and thus are closer to equilibrium relatively. We control the change of market structure due to the policy by expelling 1944 sellers sampled from those sellers who really exit and imposing all sellers to register platform refund insurance in market 1. As a result, the seller variety and platform refund insurance registration rate of counterfactual market based on market 1 are the same as those in market 48. We assume that sellers are not allowed to strategically react to the policy change in simulated market. Therefore, other characteristics of sellers in simulated market are the same with those in market 1 which is in the equilibrium before the policy change, allowing us to examine potential indirect effect by comparing the simulated market with observed market 48. Since
the direct effect of policy is well controlled, the difference only comes from the other characteristics which are not direct impacted by the policy but strategically adjusted by sellers given policy change.

The direct effect makes the whole platform lose market share of 3.22% by expelling sellers who refuse to register platform refund insurance, however, gains an additional 8.61% market share from the improved seller quality, which results in an overall 5.39% increment of market shares. It is opposite to what we observe in Figure 1 because the simulated policy only incurs loss of variety from 19.44 sellers, which is only one fifth the loss in the observation. It implies that without considering sellers’ strategic adjustment, the simulated policy change makes the market better off. Consistently, the results show CV as 0.027 (RMB), implying that improved quality sufficiently offsets the loss from less variability, which leads to an overall better off for consumers.

Given the direct effect of the policy measure, we could measure indirect effect by comparing simulated market and market 48. Our results show that in addition to the increment of market share by 5.39%, the indirect effect further increases market share by 25.36%. With regard to consumer welfare, if we set market 48 as the initial policy, CV is estimated to be -1.02 (RMB). Note that the difference between market 48 and simulated market is only about characteristics other than platform refund insurance and seller variety, which are assumed to be close to equilibrium before and after policy respectively, our findings indicate that platform and consumers are significantly better off in the new equilibrium after the policy, suggesting a potentially positive indirect effect of the policy if there is no other policy change or positive exogenous shock happens to the market that we don’t observe. Though our method is inadequate to give a conclusive explanation for the positive indirect effect, we conjecture that the “conform or to be cast out” policy in general homogenizes sellers by expelling and enforcing the same characteristics, and triggers new competitions for sellers who have motivation and ability to differentiate with others, which finally escalates the overall characteristics in the new equilibrium.

Conclusion

Unlike most physical goods, services sold in the online marketplace come with limited information about quality such that consumers are highly dependent on the reputation system and platform endorsement to choose sellers. Research is needed to help sellers and platform managers to quantify the returns based on the reputation system and platform endorsement in service marketplaces and to examine the effectiveness of related policy with the goal to improve the overall quality of consumption on the platform.

We apply a BLP-style model that recovers the demand data-generation process to study how consumer-generated reputation and platform endorsement affect the purchasing behavior of consumers and, consequently, the demand for sellers. Applying the model to aggregate-level sales data for recharging in a prepaid-phone service, we find that consumer-generated reputation significantly motivates consumers to purchase from sellers with faster delivery rates, fewer disputes, fewer required refunds and fulfilled refunds, higher average ratings, larger rating volume, and more positive evaluations and fewer negative ones. In addition, sellers’ sensitivities toward information from the reputation system are quite homogeneous, except toward the number of fulfilled refunds. In contrast, the distribution of consumers’ tastes for platform endorsements, such as coupons, short-term VIP seller tags, threshold discounts, sample gifts, accepting credit cards, and guaranteed return and exchange, is quite widespread, resulting in inconsistent marginal effects on demand across different sellers. One possible explanation might be that the benefit of a certain type of platform endorsement would be enjoyed only by a subgroup of matching consumers who favor the endorsements, while the rest of consumers would perceive platform endorsement as transferred cost and as resulting in a negative impact. With regard to platform endorsement in the case of less heterogeneity in taste, demand increases consistently when sellers register tags for platform refund insurance, VIP stores, and detailed pictures and decreases with tags of seasonal short-term sale discounts. Further, we derive self- and cross-market share elasticities of sellers’ characteristics to quantify the impact of competition when sellers adjust specific characteristics and consumer surplus to understand the overall performance of the platform in monetary units.

We use the estimate of our model to conduct an empirically oriented policy analysis of the “conform or be cast out” policy that is observed in our data. With a counterfactual simulation, we measure the direct effect on demand and consumer welfare of platform refund insurance and that of the expulsion rule. We find the externalities of both aspects of the policy, as sellers who switch to the insurance plan squeeze demand from the market share of sellers who are already in the plan, and sellers who decide to conform
and stay cannibalize the market share from sellers who exit the market. Consumers would gain additional surplus with an improved overall insurance policy of sellers, while lose some welfare due to diminishing seller variety. By combining both aspects of the policy, we find that sellers who newly switch to insurance plans would gain additional market share. The marginal impact on sellers who are already in the plan, however, varies, depending on whether the cannibalized market share from expelled sellers is enough to offset the loss from the escalated competition of platform refund insurance. Consumers are better off, given that premiums from improved insurance adequately cover the loss from a smaller selection set. Further, by controlling the state of the platform refund insurance and the variety of sellers who remain in the market, we compare markets before and after policy implementation to infer potentially indirect effects that are generated by strategic adjustment of other characteristics by sellers after the policy shock.

Our results imply that the policy triggers further competition in which sellers upgrade their characteristics. The competition, in contrast, improves the overall quality of the platform and increases consumer welfare by about 1 (RMB). Given that the policy, in general, shortens the distance between sellers in characteristic space, one possible explanation for the escalation is that sellers strategically seek to differentiate themselves after the homogenizing shock. To our knowledge, this empirical study is the first to examine explicitly the effectiveness of the “conform or be cast out” policy in the online marketplace. Although these estimates are based on the assumption of stationary, unobserved shock, they nevertheless provide the best possible estimates of further reactions of sellers and represent the process of approaching a new equilibrium after the policy change.

There are some limitations of our research. First, a more accurate and efficient model could be developed if a supply side function were incorporated. Although it may not be feasible to model a fully two-sided market, it would allow us to endogenize platform endorsement variables and sellers’ other decisions and further allow us to understand the strategic action of sellers as well as the formation of equilibrium explicitly. However, to do so poses a methodological challenge in our context, given the very large action space and very large number of players. The nonstationary evolving of the characteristics of sellers also indicates potential off-equilibrium decisions of sellers, which cast doubt on the validity of the profit maximizer assumption. We leave this issue to be addressed in empirical studies. In addition, our model has limitations with regard to the entry and exit decisions of sellers. Future research can incorporate these decisions to provide a more accurate measure of the effect of “casting out” and the overall platform evolution by endogenizing these decisions. Further, future research should investigate individual-specific purchasing decisions with additional individual-level data and demographic information, allowing estimated substitution patterns and welfare to reflect heterogeneous tastes for characteristics driven by demographics. Doing so would generate more accurate results, as it frees the model from a heavy dependence on idiosyncratic logit error (Petrin, 2002). Finally, our model and data failed to capture some other potentially important determinants, such as ranking system, although some are highly correlated with the observed characteristics in our model. Having an understanding of additional determinants and the mechanism behind the ranking system can further improve the accuracy of demand estimation. We believe that the limitations of our paper open avenues for more research in this area.
References


