# Review Rating-based Platform Screening and New Complementor Entry: Evidence from Natural Experiment and Machine Learning of a Sharing Economy

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## Abstract

Platform owners often strive to reduce adverse selection and increase quality reputation by redesigning their platforms. One such platform design is to screen incumbent complementors by ranking them based on their review ratings. We theorize that this rating-based platform screening may increase entry costs and thus has a negative effect on new complementor entry ex ante. This negative effect is further strengthened by incumbents' ratings due to strategic disadvantages for potential entrants. However, these negative effects can be rather desirable because the subsequent quality reputation of both incumbents and entrants may improve in the wake of the platform screening ex post. Our theory is supported by causal evidence from an exogenous platform design change and extensive complementor-level dataset on a major sharing economy platform. Given the tradeoff where platform screen boosts the quality of entrants at the price of quantity, we leverage a machine learning algorithm of causal forest to empower platform managers to learn the heterogeneous responses to platform screening across individual incumbents and to develop an optimal screening strategy for maximized quantity and quality of new complementor entry.



***Keywords: Entry, Ratings, Platform Design, Complementors, Screening, Sharing Economy***

## INTRODUCTION

Two-sided platforms facilitate interactions between buyers and sellers who would not transact otherwise (McIntyre and Srinivasan, 2017; Kapoor and Agarwal 2017). Examples include video consoles and games, computing platforms, and hardware/software, and recent burgeoning Uber, Lyft, Airbnb, and other sharing economy platforms. In most sharing platform ecosystems, entry cost may be low since complementors use their existing capital or labor (Einav et al., 2016).

However, severe information asymmetry exists on the platforms between users (i.e. buyers) and complementors (i.e. sellers), because product quality is uncertain for most users (Pavlou and Gefen 2004). This, in turn, may lead to opportunistic behavior by complementors (Dellarocas 2003) and adverse selection—a phenomenon where low-quality products may drive out high-quality products (Akerlof 1970, Ghose 2009).

Therefore, platform owners often strive to reduce adverse selection and increase quality reputation by redesigning their platforms. One platform design that reduces adverse selection is to screen incumbent complementors by ranking them based on their review ratings and recommending/placing incumbents with higher (lower) ratings in the top (bottom) positions. Indeed, user-generated review ratings can provide assessments of product quality and reduce information asymmetry (Ghose et al., 2005; Pavlou and Dimoka, 2006).

In this study, we theorize that such a rating-based platform screening that directly targets incumbents may indirectly affect the entry of new complementors. We put the spotlight on new complementor entry because it is crucial for platforms' growth and network externalities (Zhu and Iansiti, 2012), which determine user adoption (Schilling, 2002; Rysman, 2009) and product innovation (Sheremata, 2004; Adner and Kapoor, 2010). This also raises the question whether such platform screening may increase or decrease the subsequent overall quality reputation of incumbents and entrants on the platform.

Our study contributes to several streams of research in information systems, strategy, and economics. First, we extend IS literature by examining the role of online reviews for new complementor entry. Previous studies have noted the role of reputation and trust in online marketplaces for user purchase decisions (Dellarocas, 2003; Dimoka et al 2012), incumbent complementors' revenues (Chevalier and Mayzlin; 2006). We theorize that online review rating information about incumbents reduces new entry since it increases incumbents' strategic advantages over entrants.

Also, the strategy literature examines how new complementors can be increased by adjusting platform features such as openness (Boudreau, 2010), introductory pricing (Clements and Ohashi, 2005), maturity (Rietveld and Eggers, 2017), and integration in the ecosystem (Li and Agarwal, 2016). Intuitively, one may expect that to the extent that platform screening increases incumbent quality, it may also attract more new complementors. Extending these studies on increasing complementors, surprisingly, we find that such platforming screening might decrease new entrants and that there is an additional negative moderating effect due to heterogeneity in incumbents.

In addition, the economics literature investigates the adverse selection “lemons” problems in insurance (Filkenstein and Poterba, 2004), wholesale car (Genesove, 1993; Certo, 2003; Benner and Zenger, 2016), and capital markets (Shane and Cable, 2002). There is a potential market failure in which products of only low-quality are traded and potential entrants may not choose to join the platform (Akerlof, 1970). Extending these studies on the demand side and the effect on prices (Dewan and Hsu, 2004) and time to sell (Ghose, 2009), we explore the supply side on how platform screening for incumbents can affect the entry of new complementors. Relatedly, empirical studies on screening and regulation of new entry have shown negative or zero effect on marketplace quality (Kugler and Sauer, 2005). Instead, we show that platform screening may increase the overall quality of the marketplace ex post. We also leverage a machine learning algorithm of causal forest to learn the heterogeneous responses to platform screening across individual incumbents and to develop an optimal screening strategy for maximized quantity and quality of new complementor entry.

## THEORY AND HYPOTHESIS DEVELOPMENT

Uncertainty about sellers' product quality may lead to platform failure because new users would not be willing to join the marketplace and current users would leave the platform (Akerlof, 1970). Further, it creates an incentive for opportunistic behavior by complementors (Dellarocas, 2003). Therefore, platform may deploy various mechanisms to screen incumbents and reduce information asymmetry between users and complementors. Ample theoretical literature has examined platform designs with incentive schemes as a screening mechanism that sacrifices the low-quality complementors (Riley, 2001). Indeed, Leland (1979) posits a theoretical model, in which an entry regulation policy in the form of licensing may mitigate the negative effects of the lemons problem. Shapiro (1986) shows that such licensing may induce investments in higher quality. On the other hand, screening new entry might also reduce quality in the market since it reinforces incumbents' strategic advantages (Stigler, 1971; Kugler and Sauer, 2005).

In this study, we examine the role of platform design that reduces adverse selection by screening incumbent complementors, i.e., by ranking them based on their review ratings and placing incumbents with higher (lower) ratings in the top (bottom) positions. We develop several hypotheses concerning the direct and moderated effects of rating-based platform screening on new complementary entry, as well as the subsequent quality reputation of both incumbents and entrants in the wake of the platform screening.

We propose that rating-based platform screening may function as an entry regulation mechanism and reduce new entry in platforms. Platforms may want to lower information asymmetry by recommending high-rating incumbent complementors and placing them with top positions to attract users. Incumbent complementors who have been highly rated by a large number of satisfied users are perceived as high quality complementors (Ghose, 2009) and are recommended and rewarded by the platform screening with top positions. In other words, after the implementation of rating-based platform screening that places high-quality incumbents on the top positions, it is easier for users to research complementor choices and purchase from high-quality incumbents, i.e., higher entry costs for new entrants (Leland, 1979; Klemperer, 1987), which may reduce new complementor entry on the platform ex ante.

H1: ceteris paribus, a rating-based platform screening for incumbent complementors will have a negative effect on new complementor entry on the platform ex ante.

We further propose a moderating role due to the heterogeneous quality of incumbent complementors. More specifically, in markets with more high-rating incumbents, the negative effect in H1 will be strengthened with further reduced new complementor entry. This is because users often rely on ratings to learn about complementors' quality, and the higher ratings a particular complementor has, the higher the trust is for that incumbent (Chen et al. 2004; Chevalier and Mayzlin, 2006; Li and Hitt, 2010). As such, the more the high-rating incumbents on the platform, the more likely the platform screening design that provides them with higher visibility will increase sales and market share for such incumbents (Caminal and Vives, 1996; Hellofs and Jacobson, 1999; Zhu and Zhang, 2010), i.e., more strategic disadvantages for new entry, which may further reduce new complementor entry on the platform ex ante.

H2: The rating-based platform screening for incumbent complementors will have a stronger negative effect on new complementor entry when the incumbents have higher ratings on the platform ex ante.

Moreover, we posit that the platform screening will improve the subsequent quality reputation of both incumbents and entrants. Such quality increase will be a result of strategic responses from both incumbents and entrants. That is, incumbents will respond to platform screening by exerting more efforts and increasing their quality to sustain high visibility and ranking position on the platform. Indeed, better quality ratings reward incumbent complementors with better competitive positions and more sales revenues on the platform (Agarwal et al, 2011; Shapiro, 1986; Zhu and Zhang, 2010). Thus, the quality reputation of incumbents will likely improve in the wake of the platform screening ex post.

On the other hand, platform screening may also function as an entry regulation that deters low-quality entrants and attracts high-quality entrants (Leland, 1979; Kleiner and Kudrle, 2000; Kugler and Sauer, 2005). Specifically, platform screening that provides high-quality incumbent complementors with better ranking position advantages will increase switching costs for users to purchase from low-quality entrants as opposed to from high-quality incumbents ex ante (Arbatskaya, 2007). Also, under such platform screening, the lower-quality new complementors, even if entered, would not survive on the platform after entry ex post, given the strategic advantages of high-quality incumbents. Hence, platform screening may attract high-quality entrants, which would suggest that the quality reputation of entrants will improve (thus less adverse selection) in the wake of the platform screening ex post as well.

H3: The subsequent quality reputation of both incumbents and entrants will improve in the wake of the platform screening ex post.

## METHODS

### Setting and Data

In testing the hypotheses with causal evidence, our setting exploits a natural quasi-experiment with an exogenous change in platform design. This platform redesign allows us to gauge the causal effect on new complementor entry. Also, our rich proprietary data set is from a large sharing economy platform. Sharing platforms differ from other two-sided platforms (e.g. video consoles and games) since complementors utilize existing capital to offer products and services (Zervas et al, 2017), and entry cost is low for sellers (Einav et al. 2016). Our sharing platform uses a location-based mobile app which connects small-scale entrepreneurial complementors, who provide home-cooked food, and nearby end users. This business was founded in Beijing, China in September 2014. After that, new complementors and users have been constantly joining the platform. Thus, this business has now been expanded to six cities nationally, and it is currently the largest home-cooked food sharing business in China.

Typically, there are four steps in connecting complementors with users on this app platform. First, the platform allows complementors to upload dishes to their online kitchens for users to make a purchase. Second, the platform allows users to observe nearby complementors and select their preferred dishes from preferred complementors and to place orders and make payments. Third, complementors prepare dishes accordingly in their home kitchens and arrange a third-party company to deliver the cooked meals to users. Fourth, users consume the food and provide review ratings on the platform to show their overall evaluation towards complementors and meals, which are observable to all stakeholders on the app platform including potential entrant complementors.

Noteworthy, from July 1, 2016 onwards, the platform implemented a rating-based screening mechanism to sort complementors and recommend high-rating complementors to users. This screening design is intended to reduce adverse selection, as it screens incumbent complementors by ranking them based on their review ratings and placing incumbents with higher (lower) ratings in the top (bottom) positions on the app platform. Before this change, the platform recommends nearby complementors to users regardless the review ratings. After it, the platform recommends nearby complementors who have highest review ratings first.

Thus, the platform screening design provides top-rating complementors with higher visibility and position advantages when users research complementors and product offerings on the app. As there were no information leaks before the platform screening change and this change was applied to all complementors and users, the platform screening change is exogenous to both complementors and users, allowing for causal inference in our hypothesis testing.

To test our hypotheses, we assemble a large dataset consisting of 2,289,661 observations for 9,831 individual complementors across 275 days from April 1st to December 30th 2016. This observational window covers both the pre- and post-policy days of the platform screening policy change.

## Dependent variable

For testing H1 and H2, we are interested in the new complementor entry to the platform. Thus, we construct the dependent variable, $S\_SEL\_NEW\_CNT_{it}$, as the number of new complementors who locate in complementor *i*'s district and join the platform to start their business on day *t*. For testing H3, we have the average number of review stars (with a max of 5), $S\_RVW\_STR_{it}$, for both incumbents and new complementors as the dependent variables.

## Independent variables

To test our hypotheses, we construct the independent variable for the rating-based platform screening change $PSC_t$, which is a binary variable set to one for the post-policy days (from July 1, 2016 onwards) and zero for the pre-policy days (before July 1, 2016). We also construct the interaction term $S\_RVW\_STR_{it} \times PSC_t$, measured as the number of review stars of incumbent complementor multiplied with *PSC*.

## Control variables

Because the dependent variable could also be affected by other factors, we include many control variables. These include: (1) $S\_RVW\_CNT_{it}$, the total number of reviews received by complementor $i$ on day $t$, implying the level of potential buyer attention to complementors; (2) $S\_RVW\_NEW\_CNT_{it}$, the number of new reviews received by complementor $i$ on day $t$, implying the daily buyer activeness; (3) $S\_DSH\_CNT_{it}$, the number of dishes offered by complementor $i$ on day $t$, implying the product diversity offered by complementors; (4) $S\_DSH\_NEW\_CNT_{it}$, the number of new dishes offered by complementor $i$ on day $t$, implying new products available on the platform; (5) $S\_DSH\_PRC_{it}$, the average price of dishes offered by complementor $i$ on day $t$, implying complementors' product price level; (6) $S\_CPN_{it}$, the total value of coupons offered by complementor $i$ on day $t$, implying the promotional activities of complementors; (7) $S\_REG_{it}$, complementor $i$'s tenure on day $t$ (i.e., number of days since registration), capturing the experience of complementors; (8) $S\_DEL\_RDS_i$, complementor $i$'s delivery radius (i.e., the maximum geo-distance (in meters) within which complementor $i$ will take orders), implying the average market scope of complementors; (9) $S\_DEL\_FEE_i$, complementor $i$'s delivery fee if $i$ delivers food to buyers, implying the average delivery fee of complementors; (10) $S\_MAL_i$, complementor $i$'s gender ($S\_MAL_i = 1$ for males and $S\_MAL_i = 0$ for females), implying the demographic information of complementors; (11) $S\_AGE_i$, complementor $i$'s age, also implying the age information of complementors; and (12) $T_t$, a set of time dummies, which are included to capture time fixed effects related to holidays and seasonality factors. We seek to derive more accurate and reliable estimates after accounting for this comprehensive set of control variables in our models.

**Model specification**

Given that we have a rich dataset at the individual complementor level, we develop dynamic panel models of new complementor entry (*S_SEL_NEW_CNT*). Equation (1) is used to test *PSC* and the interaction effect of *S_RVW_STR* and *PSC*. Noteworthy, due to the discrete count nature of our dependent variable, we perform log-transformation to estimate a log-linear model. We also add one to the variable to avoid logarithms of zeros. In these models, $\beta$s and $\lambda$ are the coefficients to be estimated, $\mu$ is the random error term as follows:

$$
\begin{aligned}
&\ln\left(S\_SEL\_NEW\_CNT_{it}+1\right)\\
&\quad=\beta_0+\beta_1 S\_RVW\_STR_{it}\times PSC_t+\beta_2 PSC_t\\
&\quad+\beta_3 S\_RVW\_STR_{it}+\beta_4 S\_RVW\_CNT_{it}+\beta_5 S\_RVW\_NEW\_CNT_{it}\\
&\quad+\beta_6 RPR_t+\beta_7 S\_DSH\_CNT_{it}+\beta_8 S\_DSH\_NEW\_CNT_{it}\\
&\quad+\beta_9 S\_DSH\_PRC_{it}+\beta_{10} S\_CPN_{it}+\beta_{11} S\_REG_{it}\\
&\quad+\beta_{12} S\_DEL\_RDS_i+\beta_{13} S\_DEL\_FEE_i\\
&\quad+\beta_{14} S\_MAL_i+\beta_{15} S\_AGE_i+T_t\lambda+\mu_{it}
\end{aligned}
\tag{1}
$$

In the robustness checks section, we include additional controls at the district level such as the number of incumbent complementors and their aggregate sales. Including these additional controls does affect the results.

## RESULTS

Table 1 presents the descriptive statistics and correlations of our model variables. As indicated, our large sample has 2,289,661 observations covering 9,831 individual complementors across 275 days. On average, there are about 3 new complementor entering into an average complementor’s district every day. On average, the complementor is 41 years old and receives 3.209 review rating stars, 152.425 total reviews and 0.321 daily new reviews. An average complementor provides 18.270 dishes with an average price of 23.080 RMB and offers 5.283 RMB coupon values for promotions. On average, complementors have joined the platform for 275 days.

[Insert Table 1 here]

We first estimate a fixed effects model of Equation (1) and summarize the results in Table 2, Column (1). As indicated, the coefficient of *PSC*, -0.064, $p < 0.01$, is negative and statistically significant. Thus, the implementation of new platform design has a negative impact on new complementor entry, supporting H1. Besides the statistical significance, we also calculate the economic significance. Based on these log-linear model estimates, we find that compared to before the platform screening, the implementation of the platform screening policy decreased new complementor entry by 6.4 percentage points each day on the platform.

Furthermore, to test the interaction effect of *S_RVW_STR* and *PSC*, we summarize the results in Table 2, Column (2). As shown, the coefficient of *S_RVW_STR* × *PSC*, -0.001, $p < 0.05$, is negative and statistically significant. Hence, the negative moderating role of high-ratings of incumbents is also supported, such that the negative effect of *PSC* would be strengthened in markets where the incumbents tend to have higher ratings. Economically, it means that for any additional 30% increase (about one star increase) in incumbent ratings, there would be additional 3% more drop of new complementor entry on the platform. Thus, H2 is also supported by the data.

[Insert Table 2 here]

We test the effects of platform screening on the subsequent quality reputation of both incumbents and entrants. In Table 3, we show how the platform quality (as measured by ratings) changed before and after *PSC*. We can see that platform screening indeed increased the overall average quality of the platform ($p<.001$). Interestingly, despite few numbers of entrants to the platform, the new complementors after the *PSC* tend to have higher quality reputation than the counterparts before it ($p<.001$). Also, the incumbent complementors on the platforms also increased their quality ratings ($p<.001$) in the wake of platform screening change. Thus, H3 is supported by the data. This means that although the platform screening reduces new complementor entry, this negative effect can be rather desirable because there are fewer low-quality entrants and more high-quality new complementors; thus, the subsequent quality reputation of both incumbents and entrants has improved, i.e., less adverse selection, in the wake of the platform screening ex post.

[Insert Table 3 here]

**Machine Learning for Optimal Platform Screening**

Thus far, our results suggest that there is a tradeoff, where platform screen can boost the quality of entrants at the price of quantity. While the platform screening might inadvertently reduce the number of new complementor entry, such reduction is not undesirable to the extent that the quality reputation of both incumbents and entrants increases after the platform screening. However, prior research notes that for platform ecosystems to be successful, the platform managers should attract more *and* high-quality entrants for indirect network effects (Rochet and Tirole, 2003; Cennamo and Santalo, 2013; Boudreau, 2010; Rysman, 2009). Thus, ideally, platform managers should maximize both quantity *and* quality of new complementor entry, conditional on the heterogeneous incumbents. Motivated by this managerial insight, we leverage a state-of-the-art machine learning algorithm of causal random forest with honest tree (Wager and Athey 2017) to develop an optimal screening strategy.

Intuitively, because individual incumbents are different from each other and have heterogeneous responses to platform screening, this causal forest algorithm can empower the platform managers to learn the heterogeneity and leverage the best combination of incumbent complementors' feature variables (such as age, gender, platform tenure, number of dish offerings, and prior review ratings). The causal forest approach to the optimal rule is advantageous here because unlike traditional regression models, it does not assume any linear or nonlinear combination of feature variables that regulate the effects of platform screening. Rather, it is a nonparametric tool and can decompose the average effects of platform screening into infinite combinations of heterogeneous effects by relentlessly (brutal force) learning and splitting the data on the feature variables of individual incumbents.

Mathematically, we denote ($X_i$, $Z_i$) as independent samples that include individual incumbents' feature variables of $X_i$ and the new complementor entry's size and rating quality variable of $Z_i$, and $W_i$ as the dichotomous variable of platform screening for the causal classification and regression tree. The random forest algorithm can recursively split the feature space of samples until we reach a set of leaves L, each of which only contains a few training samples. Then, given a test point $x$, we can evaluate the prediction $\hat{\delta}(x)$ by identifying the leaf $L(x)$ containing $x$ and setting:

$$\hat{\delta}(x) = \frac{1}{|\{i: X_i \in L(x)\}|} \sum_{\{i:X_i \in L(x)\}} Z_i \tag{2}$$

The causal forests assure that the leaves of each tree are small enough so that the ($Z_i$, $W_i$) pairs correspond to the indices $i$ for $i \in L(x)$ as if in a randomized experiment with a balanced sampling and splitting (i.e., so-called honest trees). Then, it estimates the causal effect for any $X_i \in L(x)$ as:

$$\hat{z}(x) = \frac{1}{|\{i: W_i = 1, X_i \in L\}|} \sum_{\{i: W_i = 1, X_i \in L\}} Z_i - \frac{1}{|\{i: W_i = 0, X_i \in L\}|} \sum_{\{i: W_i = 0, X_i \in L\}} Z_i \tag{3}$$

After causal random forest generates an ensemble of B trees, each of which casts a vote with an estimate $\hat{\gamma}_b(x)$, the forest then aggregates their predictions of heterogeneous treatment effects by averaging these votes: $\hat{z}(x) = B^{-1} \sum_{b=1}^{B} \hat{z}_b(x)$. It has been shown that the estimates from causal forest algorithm are pointwise consistent to gauge the true treatment effect, with an asymptotically Gaussian and centered sampling distribution (Wager and Athey 2017).

We implemented the causal forest algorithm in the *RStudio*. The results indicated that, for the platform screening to attain the maximized quantity *and* quality of new complementor entry, the platform should target markets where the incumbents should be 33 to 46 years old, female, with 17 to 25 weeks of platform tenure, 15 to 28 dish offerings on the menu, and 3.85 to 4.53 review rating stars *simultaneously*.

**ROBUSTNESS CHECKS**

Here we provide additional measures to establish the robustness of our results. First, after having employed fixed effects model for the above analysis, we now utilize a random effects model and summarize the results in Table 2, Columns (3) and (4). As indicated, all the results remain consistent. In order to choose between fixed effects and random effects models, we also perform the Hausman test; the results for the main effect model ($\chi^2 = 150.19$, $p = 0.000$) and interaction effect model ($\chi^2 = 171.16$, $p = 0.000$) suggest that the fixed effects model should be chosen over the random effects model.

Second, because our dependent variable is a count variable, we also employ count data models for estimation. We thus estimate a fixed effects Poisson model and summarize the results in Table 2, Columns (5) and (6). Both the main and interaction effects remain consistent. Thus, all our hypotheses are robust to Poisson model estimation.

Third, we employ a fixed effects negative binomial model that accounts for the potential over-dispersion issue of the dependent variable. The main and interaction results in Table 2, Columns (7) and (8), are still consistent. Thus, our hypotheses remain robust to negative binomial model estimation.

Furthermore, we use additional explanatory variables such as lagged sales revenues (proxy for market power of incumbents), inventory level (proxy for capacity constraint of incumbents) and rating standard deviation (proxy for dispersion of the quality of incumbents;

we control for both rating volume and dispersion when testing the moderating role of complementor ratings ), all of which may affect new complementor entry (*S_SEL_NEW_CNT*). We find similar results in Table 4, which consistently support our hypotheses.

[Insert Table 4 here]

Finally, we perform two additional robustness checks by altering the level of analysis. First, we analyze at the aggregated district level by using the dependent variable, the number of new complementors in district m and time t, ln($D\_SEL\_NEW\_CNT_{mt}$ + 1), as opposed to our main results at the individual level, $S\_SEL\_NEW\_CNT_{it}$, in equation (1). Independent variables include *D_RVW_STR* which is the average number of stars of all incumbent complementors in district m in time t, *PSC* is as defined above, and *D_RVW_STR* × *PSC* is the interaction term. Control variables include *D_SEL_CNT* which is the number of incumbent complementors, *D_REV* is the aggregate sales of all complementors in district m and max number of reviews and review stars across all complementors in district *m* in time *t*. We summarize the results of this model specification in Table 5 Panel A. The results are similar to our main specification and support our hypotheses. Second, we use an additional specification in which we combine the main specification of equation (1) with additional controls at the district level. We summarize the results in Table 5 Panel B. The results indicate that *PSC* has a negative effect, and the interaction term (*S_RVW_STR* × *PSC*) also has a negative effect, again consistently supporting our hypotheses.

[Insert Table 5 here]

## DISCUSSION AND SUMMARY

This paper provides a new dimension about the impact of platform screening for incumbents on entrants. We use the context of sharing economy platforms to test our hypotheses. These online marketplaces have affected how a community of users and entrepreneurial complementors interact and exchange otherwise underutilized capital. We exploit an exogenous rating-based platform design change and extensive complementor-level data to demonstrate causal and robust evidence.

Our study is the first to empirically uncover the deterring role of platform design for new complementor entry. Platforms adjust their rating reputation systems to reduce information asymmetry between users and complementors. Previous studies have examined indirect network effects or incumbents' implications for new complementors (Boudreau, 2010; Rochet and Tirole, 2003; Kapoor and Lee, 2013; McIntyre and Srinivasan, 2017; Zhu and Iansiti, 2012), but not the role of user ratings platform design and incumbents' rating advantages over new entry. We reveal that a rating-based platform screening may actually increase entry costs and, thus, has a negative effect on new complementor entry. This negative effect is further strengthened by incumbents' ratings due to strategic disadvantages for potential entrants. In addition, we show that platform screening affects the quality distribution on the platform: these negative effects can be quite desirable because the subsequent quality reputation of both incumbents and entrants may improve in the wake of the platform screening.

There are some important managerial implications of our work. Managers should acknowledge that platform screening design can be a crucial factor for new complementor entry and overall quality. Also, complementor entry depends on the interaction between platform design and incumbent heterogeneity. Since new complementors are independent firms that follow their own strategies, they may also evaluate their future competitors' market power in the case of entry. After all, entry does not depend only on which platform screening design but also on the heterogeneous quality of incumbent complementors. However, given that there is a tradeoff that platform screen can boost the quality of entrants at the price of quantity, we leverage a machine learning algorithm of causal forest. This algorithm can empower the platform managers to learn the heterogeneous responses to platform screening across individual incumbents and develop an optimal screening strategy, which can maximize *both* quantity and quality of new complementor entry, rather than one at the price of the other.

There are some possible extensions for future research. This study has focused mainly on complementor entry, and thus has not examined prices or product differentiations. It is plausible that product differentiations may make entry more likely and help incumbents hold their existing market shares in market equilibrium. Prices are important for existing users and new users when comparing with offline product choices. Prices also determine whether potential entrants can compete with incumbents in an ex post market structure. As network externalities play an important role for users, if a certain platform design is an entry barrier for new complementors, this implies that users receive less network externalities. Further, fewer complementors on the platform may imply more market power for incumbents, who may have the ability to charge higher prices for their products and services in equilibrium. This issue is related to consumer welfare and how much consumer surplus incumbents may extract from users given entry barriers for new entrants, thus an important area for future work.

In addition, we did not examine how other platform characteristics affect new firm entry, such as the role of certifications for incumbents and entrants. These platform characteristics may be market-driven rather than centrally planned by the platform. They can go beyond the consumer rating reviews in order to reduce information asymmetry and adverse selection on the complicated platform ecosystem.

Finally, we did not examine the effects on offline firms. Platform-based markets often rival directly with offline traditional industries (i.e. Uber/Lyft and taxi industry, Airbnb and hotel industry) and have altered the competitive landscape. This might be another fruitful avenue for future research on platform designs.

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**Table 1. Descriptive statistics and correlations**

| | Variable | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | *S_SEL_NEW_CNT* (Number of new complementors) | 3.177 | 4.908 | - | | | | | | | | | | | | | |
| 2 | *S_RVW_STR* (Number of review stars) | 3.209 | 2.292 | 0.087 | - | | | | | | | | | | | | |
| 3 | *S_RVW_CNT* (Number of reviews) | 152.425 | 357.112 | -0.004 | 0.305 | - | | | | | | | | | | | |
| 4 | *S_RVW_NEW_CNT* (Number of new reviews) | 0.321 | 1.395 | 0.025 | 0.166 | 0.512 | - | | | | | | | | | | |
| 5 | *PSC* (Platform screening change) | 0.712 | 0.453 | -0.086 | -0.007 | 0.021 | 0.003 | - | | | | | | | | | |
| 6 | *S_DSH_CNT* (Number of dishes) | 18.270 | 20.104 | -0.005 | 0.270 | 0.292 | 0.323 | 0.025 | - | | | | | | | | |
| 7 | *S_DSH_NEW_CNT* (Number of new dishes) | 0.028 | 0.314 | -0.012 | 0.035 | 0.034 | 0.100 | -0.022 | 0.080 | - | | | | | | | |
| 8 | *S_DSH_PRC* (Average dish price) | 23.080 | 13.528 | 0.004 | -0.025 | -0.004 | 0.028 | 0.030 | 0.010 | 0.016 | - | | | | | | |
| 9 | *S_CPN* (Coupon value offered) | 5.283 | 31.123 | -0.048 | 0.121 | 0.392 | 0.321 | -0.024 | 0.242 | 0.071 | 0.021 | - | | | | | |
| 10 | *S_REG* (Complementor tenure) | 275.695 | 133.017 | 0.026 | 0.101 | 0.242 | -0.062 | 0.302 | 0.143 | -0.105 | -0.135 | -0.043 | - | | | | |
| 11 | *S_DEL_RDS* (Delivery radius) | 2,161.341 | 1,308.479 | 0.002 | 0.068 | 0.067 | 0.109 | 0.029 | 0.086 | 0.038 | 0.203 | 0.081 | -0.166 | - | | | |
| 12 | *S_DEL_FEE* (Delivery fee) | 2.645 | 0.756 | 0.001 | 0.180 | 0.146 | -0.012 | -0.088 | 0.151 | -0.045 | -0.075 | -0.001 | 0.407 | -0.014 | - | | |
| 13 | *S_MAL* (Gender) | 0.286 | 0.452 | -0.005 | 0.003 | 0.011 | 0.021 | 0.008 | -0.053 | 0.001 | 0.048 | 0.020 | -0.053 | 0.066 | -0.034 | - | |
| 14 | *S_AGE* (Age) | 41.305 | 12.211 | -0.016 | 0.051 | 0.069 | 0.008 | -0.024 | 0.026 | -0.010 | -0.121 | 0.001 | 0.148 | -0.139 | 0.104 | -0.077 | - |

*Note*: Number of observations = 2,289,661, number of complementors = 9,831, number of days = 275.

**Table 2. Estimation results**

| Variable | Fixed effects Log-linear model | | Random effects Log-linear model | | Fixed effects Poisson model | | Fixed effects Negative binomial model | |
|---|---|---|---|---|---|---|---|---|
| | (1) Main | (2) Interaction | (3) Main | (4) Interaction | (5) Main | (6) Interaction | (7) Main | (8) Interaction |
| ***S_RVW_STR × PSC*** | | -0.001** | | -0.001** | | -0.002*** | | -0.001*** |
| (Interaction) | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| ***PSC*** | -0.064*** | -0.061*** | -0.064*** | -0.060*** | -0.280*** | -0.275*** | -0.033*** | -0.022*** |
| **(Platform screening change)** | (0.001) | (0.002) | (0.001) | (0.002) | (0.024) | (0.040) | (0.001) | (0.005) |
| *S_RVW_STR* | 0.024*** | 0.025*** | 0.017*** | 0.018*** | 0.032*** | 0.033*** | 0.007*** | 0.009*** |
| (Number of review stars) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_RVW_CNT* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| (Number of reviews) | (0.154) | (0.104) | (0.704) | (0.573) | (0.119) | (0.047) | (0.023) | (0.044) |
| *S_RVW_NEW_CNT* | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.013*** | 0.013*** | 0.014*** | 0.014*** |
| (Number of new reviews) | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) |
| *S_DSH_CNT* | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| (Number of dishes) | (0.008) | (0.014) | (0.003) | (0.005) | (0.017) | (0.051) | (0.001) | (0.001) |
| *S_DSH_NEW_CNT* | -0.003*** | -0.003*** | -0.004*** | -0.004*** | 0.001 | 0.001 | -0.004*** | -0.004*** |
| (Number of new dishes) | (0.001) | (0.000) | (0.000) | (0.001) | (0.093) | (0.032) | (0.000) | (0.000) |
| *S_DSH_PRC* | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 | 0.000 |
| (Average dish price) | (0.533) | (0.533) | (0.137) | (0.139) | (0.119) | (0.115) | (0.004) | (0.005) |
| *S_CPN* | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.000*** | -0.000*** | -0.001*** | -0.001*** |
| (Coupon value offered) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_REG* | 0.002*** | 0.001*** | 0.002*** | 0.003*** | 0.001*** | 0.000*** | 0.002*** | 0.001*** |
| (Complementor tenure) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_DEL_RDS* | | | 0.000 | 0.000 | | | 0.006*** | 0.006*** |
| (Delivery radius) | | | (0.620) | (0.615) | | | (0.001) | (0.001) |
| *S_DEL_FEE* | | | 0.001 | 0.000 | | | 0.006 | 0.007 |
| (Delivery fee) | | | (0.922) | (0.931) | | | (0.813) | (0.967) |
| *S_MAL* | | | -0.012 | -0.012 | | | 0.001 | 0.001 |
| (Gender) | | | (0.178) | (0.179) | | | (0.782) | (0.774) |
| *S_AGE* | | | -0.002*** | -0.001*** | | | -0.001*** | -0.001*** |
| (Age) | | | (0.000) | (0.000) | | | (0.000) | (0.000) |
| Time dummies | -included- | -included- | -included- | -included- | -included- | -included- | -included- | -included- |
| Hausman test | $\chi^2 = 150.19$, $p = 0.000$ / $\chi^2 = 171.16$, $p = 0.000$ | | | | | | | |
| Number of complementors | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 |
| Number of observations | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 |

**Table 3. Effect of Platform Screening Change on Rating Quality Reputation**

| Platform Quality (as measured by ratings) | Average | Standard Deviation | t-test | p-value |
|---|---|---|---|---|
| Overall | | | | |
| Before Platform Screening | 3.2327 | 2.2843 | 138.81 | 0.0000 |
| After Platform Screening | 3.2771 | 2.2667 | | |
| | | | | |
| Incumbents | | | | |
| Before Platform Screening | 3.2342 | 2.2756 | 116.75 | 0.0000 |
| After Platform Screening | 3.2749 | 2.2616 | | |
| | | | | |
| New entrants | | | | |
| Before Platform Screening | 3.2286 | 2.3138 | 165.89 | 0.0000 |
| After Platform Screening | 3.2793 | 2.3006 | | |

*Note: 3 months before and after the policy change.*

**Table 4: Robustness checks controlling for lagged sales revenues, stock inventory, and rating dispersion.**

| Variable | Lagged sales revenue *S_REV* | | Inventory level *S_DSH_STK* | | Rating standard deviation *S_RVW_STR_SD* | | All | |
|---|---|---|---|---|---|---|---|---|
| | (1) Main | (2) Interaction | (3) Main | (4) Interaction | (5) Main | (6) Interaction | (7) Main | (8) Interaction |
| *S_RVW_STR* × *PSC* | | -0.001*** | | -0.002*** | | -0.001*** | | -0.001*** |
| (Interaction) | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| *PSC* | -0.061*** | -0.058*** | -0.064*** | -0.057*** | -0.066*** | -0.051*** | -0.063*** | -0.061*** |
| (Platform Screening Change) | (0.002) | (0.008) | (0.005) | (0.006) | (0.008) | (0.002) | (0.003) | (0.005) |
| *S_RVW_STR* | 0.029*** | 0.106*** | 0.028*** | 0.109*** | 0.052*** | 0.134*** | 0.045*** | 0.112*** |
| (Number of review stars) | (0.001) | (0.000) | (0.002) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_RVW_CNT* | -0.002*** | -0.001*** | -0.001*** | -0.000*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| (Number of reviews) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_RVW_NEW_CNT* | 0.000 | 0.004 | 0.056*** | 0.058*** | 0.061*** | 0.063*** | 0.005 | 0.008 |
| (Number of new reviews) | (0.919) | (0.297) | (0.000) | (0.000) | (0.000) | (0.000) | (0.215) | (0.051) |
| *S_DSH_CNT* | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| (Number of dishes) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_DSH_NEW_CNT* | -0.062*** | -0.064*** | -0.051*** | -0.054*** | -0.029*** | -0.035*** | -0.042*** | -0.047*** |
| (Number of new dishes) | (0.002) | (0.000) | (0.000) | (0.000) | (0.002) | (0.000) | (0.000) | (0.000) |
| *S_DSH_PRC* | 0.006*** | 0.005*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.005*** |
| (Average dish price) | (0.001) | (0.002) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_CPN* | -0.005*** | -0.005*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.005*** | -0.005*** |
| (Coupon value offered) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_REG* | 0.001*** | 0.000*** | 0.001*** | 0.001*** | 0.002*** | 0.000*** | 0.001*** | 0.001*** |
| (Complementor tenure) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_DEL_RDS* | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | 0.000 | -0.000 | -0.000 |
| (Delivery radius) | (0.002) | (0.008) | (0.117) | (0.254) | (0.779) | (0.990) | (0.471) | (0.647) |
| *S_DEL_FEE* | 0.066*** | 0.062*** | 0.063*** | 0.060*** | 0.041*** | 0.040*** | 0.043*** | 0.043*** |
| (Delivery fee) | (0.013) | (0.015) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_MAL* | -0.076*** | -0.075*** | -0.074*** | -0.073*** | -0.076*** | -0.075*** | -0.073*** | -0.072*** |
| (Gender) | (0.029) | (0.022) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *S_AGE* | -0.007*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** |
| (Age) | (0.002) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.002) |
| *S_REV* | 0.001*** | 0.001*** | | | | | 0.001*** | 0.001*** |
| (Lagged sales revenue) | (0.000) | (0.000) | | | | | (0.000) | (0.000) |
| *S_DSH_STK* | | | -0.002*** | -0.002*** | | | -0.002*** | -0.001*** |
| (Average dish stock level) | | | (0.000) | (0.000) | | | (0.000) | (0.000) |
| *S_RVW_STR_SD* | | | | | -0.236*** | -0.205*** | -0.228*** | -0.200*** |
| (Standard deviation of *S_RVW_STR*) | | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Time dummies | -included- | -included- | -included- | -included- | -included- | -included- | -included- | -included- |
| Number of complementors | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 | 9,831 |
| Number of observations | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 | 2,289,661 |

*Note*: *P* values in parentheses. * *p*<0.1, ** *p*<0.05, *** *p*<0.01.

**Table 5. Additional Results**

**Panel A: District-level analysis**

| Variable | Fixed effects log-linear model | Random effects log-linear model |
|---|---|---|
| *D_RVW_STR* × *PSC* | -0.021** | -0.020** |
| (Interaction) | (0.006) | (0.006) |
| *PSC* | -0.054** | -0.048** |
| (Platform Screening Change) | (0.023) | (0.019) |
| *D_RVW_STR* | 0.063*** | 0.037** |
| (Average review stars of complementors) | (0.006) | (0.019) |
| *D_SEL_CNT* | 0.003*** | 0.002 |
| (Number of complementors) | (0.000) | (0.035) |
| *D_REV* | 0.002*** | 0.001*** |
| (Sales revenue of all complementors) | (0.000) | (0.000) |
| *D_REV_NEW* | 0.001*** | 0.001*** |
| (Sales revenue of new complementors) | (0.000) | (0.000) |
| *D_RVW_CNT* | 0.000 | -0.000 |
| (Average number of reviews of all complementors) | (0.325) | (0.657) |
| *D_RVW_CNT_MAX* | -0.000 | 0.002*** |
| (Max number of reviews of complementors) | (0.048) | (0.000) |
| *D_RVW_STR_MAX* | 0.038*** | 0.029*** |
| (Max number of review stars of complementors) | (0.010) | (0.010) |
| *D_DSH_CNT* | -0.001 | -0.000 |
| (Total number of dishes of all complementors) | (0.025) | (0.024) |
| Time dummies | -included- | -included- |
| Hausman test | $\chi^2 = 57.72$, $p = 0.000$ | |
| Number of districts | 16 | 16 |
| Number of observations | 4,400 | 4,400 |

*Note*: *P* values in parentheses. * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

**Panel B: With Additional District-level Covariates**

| Variable | Fixed effects log-linear model | Random effects log-linear model |
|---|---|---|
| *S_RVW_STR* × *PSC* | -0.001*** | -0.001** |
| (Interaction) | (0.000) | (0.000) |
| *PSC* | -0.061*** | -0.217*** |
| (Platform Screening Change) | (0.000) | (0.000) |
| *S_RVW_STR* | 0.029*** | 0.002*** |
| (Number of review stars) | (0.000) | (0.000) |
| *S_RVW_CNT* | -0.000 | 0.000 |
| (Number of reviews) | (0.155) | (0.000) |
| *S_RVW_NEW_CNT* | 0.009*** | 0.008*** |
| (Number of new reviews) | (0.000) | (0.000) |
| *S_DSH_CNT* | 0.001*** | 0.000 |
| (Number of dishes) | (0.000) | (0.179) |
| *S_DSH_NEW_CNT* | -0.004** | -0.009*** |

| | | |
|---|---|---|
| (Number of new dishes) | (0.002) | (0.000) |
| *S_DSH_PRC* | 0.000 | -0.002*** |
| (Average dish price) | (0.468) | (0.000) |
| *S_CPN* | -0.003*** | -0.001*** |
| (Coupon value offered) | (0.000) | (0.000) |
| *S_REG* | -0.001*** | -0.002*** |
| (Complementor tenure) | (0.000) | (0.000) |
| *S_DEL_RDS* | | -0.002*** |
| (Delivery radius) | | (0.000) |
| *S_DEL_FEE* | | 0.013*** |
| (Delivery fee) | | (0.000) |
| *S_MAL* | | -0.004*** |
| (Gender) | | (0.000) |
| *S_AGE* | | -0.000 |
| (Age) | | (0.503) |
| *D_SEL_CNT* | 0.006*** | 0.001*** |
| (Number of complementors) | (0.001) | (0.000) |
| *D_REV* | 0.001*** | 0.001*** |
| (Sales revenue of all complementors) | (0.000) | (0.000) |
| *D_REV_NEW* | -0.003*** | -0.003*** |
| (Sales revenue of new complementors) | (0.000) | (0.000) |
| *D_RVW_CNT* × *PSC* | 0.006*** | 0.001*** |
| | (0.002) | (0.000) |
| *D_RVW_CNT* | 0.001*** | -0.001*** |
| (Average number of reviews of all complementors) | (0.000) | (0.000) |
| *D_RVW_STR* | -0.015*** | -0.034*** |
| (Average number of review stars of all complementors) | (0.000) | (0.000) |
| *D_RVW_CNT_MAX* | 0.002*** | 0.001*** |
| (Max number of reviews of complementors) | (0.000) | (0.000) |
| *D_RVW_STR_MAX* | 0.003*** | 0.003*** |
| (Max number of review stars of complementors) | (0.000) | (0.000) |
| *D_DSH_CNT* | -0.002*** | -0.002*** |
| (Total number of dishes of all complementors) | (0.000) | (0.000) |
| Time dummies | -included- | -included- |
| Hausman test | $\chi^2$ = 70,728.06, $p$ = 0.000 | |
| Number of complementors | 9,831 | 9,831 |
| Number of observations | 2,289,661 | 2,289,661 |

*Note*: $P$ values in parentheses. * $p$<0.1, ** $p$<0.05, *** $p$<0.01.