JOURNAL OF MANAGEMENT STUDIES

Journal of Management Studies 59:7 November 2022
doi:10.1111/joms.12807

When More is Less: Quality and Variety Trade-off in Sharing Economy Platforms

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ABSTRACT Platform owners often attempt to reduce information asymmetry between sellers and buyers by redesigning how users interact. One widely used platform design is to sort (i.e., rank) incumbent sellers based on their buyer-generated ratings within a geographical area. We theorize that this mechanism may indirectly limit the entry of low-quality sellers to the platform and therefore increase overall platform quality, but it may also reduce variety. As incumbents adjust their strategies to gain a display advantage, the competition effect functions as an additional barrier to sellers who would otherwise enter the platform. We use an extensive dataset from a sharing economy platform to identify sellers' heterogeneous strategic responses at the market level. Our results highlight that platform owners may face an unintended trade-off between product quality and variety at the local level when they design their rating systems.

Keywords: entry, platforms, quality, sharing economy, sorting, variety

INTRODUCTION

Two-sided platforms facilitate interactions between buyers and sellers who would not otherwise transact by providing a common, mutually compatible environment with low transaction costs (Adner and Kapoor, 2010; Armstrong, 2006; Autor, 2001; Hagiu, 2009; Rochet and Tirole, 2003; Rysman, 2009; Wareham et al., 2014). Examples of such platforms include video games, computing, and hardware/software; more recently, burgeoning sharing economy platforms such as Uber, Lyft, and Airbnb have become significant players in this area (Autor, 2001; Einav et al., 2016; Hall et al., 2021). It may be important for buyers who are deciding whether or not to join a platform to know the number of

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sellers (Ohashi, 2003) and the quality (Hagiu, 2009) and variety (Boudreau, 2010) they offer in a specific geographical area (Eckhardt et al., 2019; Koo and Eesley, 2021).

The goal of this paper is to provide a theoretical background and empirically test the trade-off between product quality and variety in sharing economy platforms. We argue that platforms that use a common rating-based sorting of sellers, whichs aims to decrease information asymmetry between buyers and sellers, may indirectly reduce the number of low-quality entrants. This may lead not only to higher platform quality (because incumbents increase their efforts and the entry of low-quality sellers is deterred) but also to less variety in the marketplace. This occurs because potential new sellers who would otherwise enter the market are deterred by the implicit strategic advantage provided to incumbents. In platforms in the sharing economy (where the local nature of transaction matters) we show that local seller heterogeneity affects the magnitude of this trade-off.

While previous studies have examined how platforms at the aggregate level use various tools, such as ecosystem complexity (Kapoor and Agarwal, 2017), openness (Adner and Kapoor, 2010; Boudreau, 2010), pricing (Clements and Ohashi; 2005, Rysman, 2009), and rewards (Claussen et al., 2013), this is the first paper to examine how quality and variety are *indirectly* influenced as a result of reduced entry at the *local* level. This is important because both seller quality and variety are necessary conditions for platform success (Armstrong, 2006; Hagiu and Wright, 2020; Rochet and Tirole, 2003; Schilling, 2002) and the local dimension of platform dynamics may also be significant (Koo and Eesley, 2021). Sharing economy platforms provide an ideal framework to examine how local market conditions affect the efficacy and indirect effects of platform design.[1]

On the one hand, information asymmetry between buyers and sellers on platforms stems from buyers' uncertainty about product quality. This may lead to opportunistic behaviour by sellers (Dellarocas, 2003) and adverse selection – a phenomenon whereby low-quality products may drive out high-quality ones (Akerlof, 1970; Filkenstein and Poterba, 2004; Ghose, 2009). Platforms predominantly use rating-based mechanisms to reduce this information asymmetry between buyers and sellers (Pavlou and Gefen, 2004). We argue that a popular type of rating-based mechanism may create an indirect barrier for new entrants. Reducing the number of low-quality entrants would thus improve platform performance because entry regulation not only reduces information asymmetry for existing buyers but also indirectly creates a barrier for low-quality entrants (Casadesus-Masanell and Halaburda, 2014; Hagiu, 2009; Halaburda et al., 2018; Rietveld et al., 2019).

On the other hand, platform owners are also incentivized to increase the number of sellers in the marketplace (Boudreau, 2012; Ohashi, 2003; Rochet and Tirole, 2003). In particular, buyers are more likely to join a platform due to network externalities, which are related to a higher number of sellers (Armstrong, 2006; Boudreau and Jeppesen, 2015; Cennamo and Santalo, 2013; Clements and Ohashi, 2005; Nair et al., 2004; Rietveld and Eggers, 2018) and thus greater variety on the platform (Boudreau, 2012). This implies that the number of sellers on the platform may have a positive effect on the number of buyers joining in the future and the number of potential matches in the marketplace (Armstrong, 2006; Rochet and Tirole, 2003; Rysman, 2009).

One widely used platform design that reduces information asymmetry is sorting incumbent sellers based on their review ratings and placing incumbents with higher (lower) ratings in the top (bottom) recommendation positions. Indeed, buyer-generated review ratings can provide assessments of product quality and reduce information asymmetry (Chevalier and Mayzlin, 2006; Che and Hörner, 2018; Pavlou and Gefen, 2004). We argue that by reducing information asymmetry for incumbent sellers, this sorting platform design provides them with a strategic advantage as their existing competitive position functions as an additional barrier for potential new entrants. This may lead to higher platform quality as incumbents increase their efforts but may also reduce variety by deterring those who would otherwise enter the platform.

We exploit an extensive panel dataset from a sharing economy platform and an exogenous policy change in the way consumers are matched to sellers to identify the causal effects. Specifically, the change involves a switch to a location-based sorting system that provides higher visibility for highly rated sellers in a given local market. The advantage of this dataset stems from two distinct dimensions that are rare and unique in platform studies: First, it provides us with an exogenous platform design change and, second, it exhibits variation in the local market context. Although reducing entry was not the direct goal of the platform change, this mechanism reduces the entry of low-quality sellers and eventually increases overall quality, but it also reduces product variety in the marketplace.

Our study contributes to two main streams of research. We theoretically argue and empirically show that by introducing a platform design that decreases information asymmetry, platforms may *unintentionally* face a trade-off between quality and variety. Prior literature has separately examined platform owners' strategies to increase the number of sellers, platform quality, and product variety in the online marketplace as a direct strategic choice. Platforms may aim to exclude low-quality sellers because buyers may value both the number of sellers (due to network externalities and potential matches) and the average quality of goods in the marketplace (Hagiu, 2009; Halaburda et al., 2018). However, restricting the number of sellers may also reduce product variety in the platform (Boudreau, 2012). We show that platform design that reduces information asymmetry may function as an indirect barrier for potential sellers. Therefore, rating-based sorting systems reduce information asymmetry but indirectly create additional barriers to those who would otherwise enter the marketplace.

Additionally, we contribute to the burgeoning literature on sharing economy platforms. Previous studies have examined the effects of platform entry (Benjaafar et al., 2019; Foerderer et al., 2018; Gawer and Henderson, 2007; Zervas et al., 2017) and how platform design affects incumbent sellers (Filippas et al., 2020; Hall et al., 2021), implicitly focusing on aggregate measures. Instead, we introduce the local nature of competition in these platforms and argue that both the dynamics of entry at the local level and local seller heterogeneity (not just at the aggregate level) are crucial in this process (McIntyre and Srinivasan, 2017).

THEORY AND HYPOTHESES DEVELOPMENT

Platforms function as intermediates among agents by setting a common set of rules and an infrastructure which regulates how these agents interact (Dinerstein et al., 2018;

Rochet and Tirole, 2003; Rysman, 2009). Previous studies have tended to focus on platform infrastructure design because of how it affects individual agents, platform owners, and society derives value from the marketplace (Armstrong, 2006; Filippas et al., 2020; Kapoor and Agarwal, 2017; Mayzlin et al., 2014; Rochet and Tirole, 2003). In recent years, technological advancements have introduced a new form of peer-to-peer platform (i.e., the sharing economy) whereby agents use existing capital or labor to provide goods or services (Benjaafar et al., 2019; Einav et al., 2016; Filippas et al., 2020). For instance, Uber connects sellers who have existing capital and labour (i.e., drivers) with buyers (i.e., passengers) while defining how these agents are matched and priced (Filippas et al., 2020; Hall et al., 2021).

Two-sided platforms use various tools (e.g., rating systems and matching algorithms) to manage information asymmetry between both sides of the market, and entry is facilitated as its cost is relatively low compared to more traditional platforms (Einav et al., 2016). Nevertheless, sharing economy platforms still exhibit issues related to information asymmetry that can only be partially solved through reputation mechanisms (Moreno and Terwiesch, 2014). Specifically, uncertainty about sellers' product quality could lead to platform failure because new buyers may be unwilling to join a marketplace, current buyers may abandon the platform (Akerlof, 1970; Autor, 2001), and sellers may have an incentive for opportunistic behaviour (Dellarocas, 2003). Therefore, platforms deploy mechanisms to reduce this information asymmetry between buyers and sellers. These mechanisms predominantly focus on screening sellers based on prior users' feedback (Boudreau and Jeppesen, 2015; Chevalier and Mayzlin, 2006; Chintagunta et al., 2010, Moreno and Terwiesch, 2014; Pavlou and Gefen, 2004).

Ample theoretical literature in economics has examined policy designs which use incentive schemes as a screening mechanism that sacrifices the entry or survival of low-quality sellers to reduce information asymmetry (Riley, 2001). However, these studies have found mixed effects in the trade-off between quality and variety. Leland (1979) posits a theoretical model in which an entry regulation policy in the form of licensing may mitigate the negative effects of asymmetric information in the market for 'lemons'. Shapiro (1986) shows that such licensing may induce investment in cultivating products of higher average quality. However, screening new entry might also reduce overall quality in the market as it reinforces the strategic advantages of incumbents and reduces competition (Kleiner and Kudrle, 2000; Riley, 2001).

Previous studies on platforms have provided limited results on how their strategies for mitigating information asymmetry *indirectly* affect the quality and variety of the marketplace. We examine how platform design may affect this relationship by deterring new seller entry. Platform owners have an incentive to directly increase the number of sellers as this is related to network effects (Boudreau and Jeppesen, 2015; Cennamo and Santalo, 2013; Clements and Ohashi, 2005; Nair et al., 2004), which implies greater variety, even if the product scope of individual sellers may become narrower (Boudreau, 2010), and higher innovation (Adner and Kapoor, 2010; Panico and Cennamo, 2022). However, restricting the number of sellers (Hagiu and Wright, 2020) or providing special treatment to some sellers over others (Rietveld et al., 2019) may increase the quality of matches and variety (Halaburda et al., 2018), help manage consumption complementarities between new and incumbent sellers (Casadesus-Masanell and Halaburda, 2014), and increase the introduction of new products from existing sellers (Hagiu and Wright, 2020).

In addition, the above studies examine the effects at the aggregate (i.e., platform) level. Instead, we introduce the local nature of competition in platforms. In sharing economy platforms, in particular, the local nature of the product may also be important as users take into account sellers' characteristics and features in a specific local market and not just aggregate measures of platform performance (Einav et al., 2016; Filippas et al., 2020; Hall et al., 2021; Zervas et al., 2017). Studies on sharing economy platforms have focused on the entry of the platform itself in the marketplace (Foerderer et al., 2018; Gawer and Henderson, 2007; Zervas et al., 2017), platform owners' optimal pricing strategies (Dinerstein et al., 2018; Hall et al., 2021), and the effect of peer-to-peer product sharing on social outcomes (Benjaafar et al., 2019; Filippas et al., 2020). However, we argue that rating-based platform design indirectly affects quality and variety at the local market level through deterred entry and local seller heterogeneity.

In summary, the previous literature has not examined how mechanisms that reduce information asymmetry, such as sorting incumbent sellers, may affect the relationship between quality and variety. We claim that indirect entry deterrence and seller heterogeneity drive this trade-off. Additionally, studies of sharing economy platforms have not examined the local dimension of competition and its role in variety and quality. In this paper, we hypothesize that location-based sorting indirectly reduces new entry and that local market conditions (such as seller composition) moderate the effect of the sorting mechanism.

Sorting and Entry

Platforms may reduce information asymmetry between buyers and sellers in the marketplace by recommending highly rated incumbent sellers and displaying them in the top positions on their platforms (Li et al., 2018). This mechanism is based on historical data about incumbent sellers in the marketplace provided by previous buyers' ratings of the product or service or the buyers' purchase history (Ansari et al., 2000; Fleder and Hosanagar, 2009). The implementation of a rating-based sorting algorithm that prioritizes highly ranked (i.e., high-quality) incumbents enables buyers to discern seller quality and to purchase from high-quality incumbents (Autor, 2001). For example, the platform may automatically sort sellers in a local market by their average rating and thereby give them increased visibility. In sharing economy platforms, this creates a ranking of top sellers in each local market. In other words, it involves recommending sellers who are not only highly rated but also belong to buyers' geographical market (Filippas et al., 2020; Hall et al., 2021).

We argue that a location-based sorting system provides an indirect strategic advantage to incumbents and creates a barrier to potential new entrants, which results in a reduced entry rate. There are several reasons why this might happen. First, incumbent sellers with many highly rated transactions are perceived as high quality (Chevalier and Mayzlin, 2006; Chintagunta et al., 2010; Ghose, 2009; Zhu and Zhang, 2010) and tend to have higher future sales. Sorting can reduce search costs for these high-reputation sellers as reputation is a market mechanism that can alleviate information asymmetry, albeit an imperfect one (Dellarocas, 2003; Pavlou and Gefen, 2004). This implies that online reviews for already successful sellers affirm their position in the marketplace and attract additional future buyers. Therefore, sorting reduces the potential demand for new entrants, which is a major determinant of new entry in a market (Bresnahan and Reiss, 1991).

Second, the placement of a product on a platform's display can itself affect its sales (Tucker and Zhang, 2011) and boost profits by increasing the search costs for consumers looking for other products (Arbatskaya, 2007). Incumbents who have higher visibility due to this exogenous placement advantage increase their revenues while new entrants with lower visibility may face lower demand ex post, which reduces their profitability and likelihood of survival (Bresnahan and Reiss, 1991; Geroski, 1995).

Additionally, historical data exists for the prior perceived product quality of incumbent sellers, while new entrants have not yet been tested or become established in the marketplace (Fleder and Hosanagar, 2009). As there is insufficient information about potential entrants, incumbents' prior market position will be reinforced, and new entrants will not be recommended, even if they are or have the potential to be high quality post entry. Historical data on buyers and sellers are more easily collected, assembled, and utilized in technology-based sharing economy platforms compared to traditional platforms (Horton and Tambe, 2015).

Therefore, a location-based ranking system may increase visibility for highly ranked incumbents and reduce information asymmetry, but it may also create a barrier for potential entrants because of their reduced potential market, placement disadvantage, and lack of historical data. In other words, although information asymmetry is reduced, the competitive position of incumbent sellers is reinforced. Therefore, we expect this location-based ranking system to indirectly reduce the entry of new sellers:

Hypothesis 1: A sharing economy platform's switch to a location-based sorting system has a negative impact on the entry of new sellers.

Local Seller Heterogeneity

We argue above that the types of sorting system used by platforms to reduce information asymmetry may harm new entrants by decreasing search costs for incumbent sellers. Next, we argue that local seller heterogeneity (such as a high proportion of highly rated incumbents) in a local market makes the entry of new sellers even less likely.

Studies on platforms usually examine the effects of strategic variables such as user preferences, network effects, and platform design on aggregate platform performance (Boudreau, 2010; Boudreau and Jeppesen, 2015; Rietveld and Eggers, 2018; Rietveld and Schilling, 2021). Most of these studies neglect to examine the local nature of competition in platforms and seller composition and heterogeneity (Koo and Eesley, 2021; Lanzolla and Frankort, 2016; McIntyre and Srinivasan, 2017). Consumers may only purchase products that are available in specific local markets and seller quality composition varies from market to market. Sharing economy platforms, in particular, may provide the appropriate framework to examine the role of seller composition across local markets as agents' decisions (e.g., location choice and service area) occur locally (Einav et al., 2016; Filippas et al., 2020; Hall et al., 2021; Zervas et al., 2017).

Users often rely on ratings to learn about sellers' quality; the higher the rating of a particular incumbent seller, the higher the trust and sales demand is for that incumbent (Chevalier and Mayzlin, 2006; Li and Hitt, 2010; Zhu and Zhang, 2010). This overall satisfaction with incumbent sellers is the result of accumulated past experience, which is likely to be persistent (Anderson et al., 1994; Garbarino and Johnson, 1999). When a platform promotes existing highly regarded sellers this reaffirms their customers' trust (Garbarino and Johnson, 1999) and engagement (Pansari and Kumar, 2017). This implies that the more high-quality incumbents there are in a market, the harder it is for new entrants to acquire customers' trust and gain market share ex post (Brensahan and Reiss, 1991; Geroski, 1995; Weigelt and Camerer, 1988). Additionally, the higher the number of high-quality incumbents, the higher the market share they collectively enjoy in the marketplace and the lower the potential demand for new firms (Bresnahan and Reiss, 1991; Caminal and Vives, 1996; Hellofs and Jacobson, 1999; Zhu and Zhang, 2010).

These factors imply that seller quality composition in a local market increases the strategic disadvantages for new entry, which may reduce new seller entry to the platform ex ante. We argue that in markets with more highly rated incumbents, the negative effect of H1 will be strengthened, leading to a greater reduction in new seller entry. In other words, higher visibility for highly rated sellers reinforces their market position and reduces the residual demand for new sellers:

Hypothesis 2: The location-based sorting system for incumbent sellers will have a stronger negative effect on new seller entry when the incumbents have higher ratings in the local market.

EMPIRICAL APPROACH

Setting and Data

The sharing platform that serves as the context of our study uses a mobile app to connect small-scale entrepreneurial sellers offering home-cooked food with local buyers. It can be characterized as part of the sharing economy because the sellers are individual entrepreneurs who leverage underutilized resources, such as spare time and home kitchens, to cook for peer-to-peer business exchanges (Zervas et al., 2017) rather than for professional restaurants or food stores on Uber Eats or Grubhub. This business was founded in Beijing, China, in September 2014 and has since expanded to six cities nationally to become the largest home-cooked food sharing business in the country.

The platform connects sellers with buyers in four steps. First, sellers upload pictures and descriptions of dishes to their 'online kitchens' – their seller's page on the platform – from which buyers can make a purchase. Second, the platform allows buyers to search local sellers, order their preferred dishes from their chosen seller, and make payment. Third, sellers prepare the dishes in their kitchens and arrange for a third-party company to deliver cooked meals to the buyers. Fourth, buyers consume the food and evaluate the seller and the meal through recommendation ratings (i.e., review stars), which can be seen by all stakeholders on the platform, including potential sellers and buyers.

Beginning 1 July 2016, the platform implemented a location-based rating system (the review popularity recommendation (RPR)) to recommend highly rated sellers to buyers within their geographical area. This system uses historical ratings to rank sellers based on their review stars and places incumbents with higher (lower) ratings in the top (bottom) positions on the app platform. Before this change, the platform recommended local sellers to buyers regardless of their ratings. Since implementing this change, top-rated sellers have been given higher visibility and positional advantages when buyers research sellers and product offerings on the app. Therefore, the change in platform design focuses on the geographical sorting of sellers. Some platforms may also learn from an individual buyer's prior purchases, but we have no evidence that this occurs in this case.

To test our hypotheses, we utilize a large dataset for 9,831 individual sellers over 275 days from 1 April to 30 December 2016. Therefore, this observational window covers the periods immediately before and after the policy change to the location-based ranking system. We aggregate the data at the district level, which is the definition of the market we consider. The sample features 4,273 observations covering 16 districts across 275 days.

Variable Description

We are interested in new seller entry to the platform at the district level. Thus, we construct the dependent variable *lnSEL_N* to represent the total number of new sellers who enter district *m* and join the platform to start their business on day *t*. We construct the independent variable *RPR* for the rating-based platform sorting change; this is a binary variable set to one for the post-policy change days (from 1 July 2016 onwards) and zero for the pre-policy change days (before 1 July 2016). *Rating* denotes the average stars for sellers in a district and is our proxy quality measure for sellers on the platform. We also construct the interaction term *Rating* x *RPR*, measured as an incumbent seller's number of review stars multiplied by *RPR*.

We include various factors as control variables at the district/day level. These include: *lnSEL*, the total number of sellers in a market; measures of demand such as *Market_size*, the total revenues in a market, *Orders*, the total number of orders in a market and *Platform_size*, the total revenues in the platform; *lnReviews*, the average number of reviews on day *t*, implying the level of potential buyer attention for existing sellers; *lnDishes*, the average number of dishes offered in district *m* on day *t*, implying the product diversity offered by existing sellers; and *lnDish_N,* the number of new dishes. These latter variables measure variety and newly introduced products. Additionally, we use *lnDish_price*, the average price of dishes offered in district *m* on day *t; lnSales*, the average seller revenue; *lnCoupons,* the average total value of coupons offered in district m on day t, implying the promotional activities of existing sellers; *lnTenure*, the average seller tenure in district m on day t (i.e., the number of days since registration), implying the experience of existing sellers; *Male*, the male ratio in district m, and *Age*, the average seller age in district m, both offering demographic information on existing sellers; and T_t, time fixed effects with day-level dummies to control for the effects of time trends, seasonality, and holidays.

Table I provides the variable definitions and descriptive statistics. Table II shows the correlations of our model variables. Note the negative correlation between *RPR* and new sellers. (−0.067, *lnSEL_N*) and new dishes (−0.071, *lnDish_N*).

Model

Our setting exploits an exogenous platform design change, which affects how buyers are informed about local sellers. Although we do not have knowledge of the rationale for this policy implementation, it is reasonable to assume that sellers did not influence this change and that the direct goal was to reduce information asymmetry. Additionally, to the best of our knowledge, there were no information leaks before the platform sorting change and no other significant events coinciding with it, which suggests that the change was exogenous to (or not expected by) both sellers and buyers. Thus, this policy change enables us to draw causal inference regarding the

Table I. Variable definitions and summary statistics

Variable	*Definition*	*Mean*	*SD*
RPR	Dummy, post-RPR period	0.69	0.46
lnSEL_N	Log (New sellers in market)	0.29	0.64
Market_size	Total revenues in market (000s)	19.94	42.86
Orders	Total orders in market (000s)	0.46	0.98
Platform_size	Total revenues in platform (000s)	309.77	101.23
lnSEL	Log (Total sellers in market)	4.02	2.61
Rating	Average review rating of sellers in market; quality	2.70	1.37
lnReviews	Log (Average number of seller reviews in market)	3.56	1.91
lnDishes	Log (Average number of dishes in market); variety	2.57	0.73
lnDish_N	Log (Average number of new dishes in market); variety	0.29	1.69
lnDish_price	Log (Average dish price in market)	3.23	0.23
lnSales	Log (Average seller revenues in market)	2.23	1.65
lnCoupons	Log (Average coupon value in market)	0.96	0.88
lnTenure	Log (Average seller tenure in market)	5.26	0.61
Male	Male sellers ratio	0.38	0.27
Age	Average age of sellers in market	38.4	7.9

Table II. Correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) RPR	1.000															
(2) lnSEL_N	−0.067	1.000														
(3) lnDish_N	−0.071	0.653	1.000													
(4) Rating	0.021	0.147	0.318	1.000												
(5) Market_size	−0.026	0.574	0.703	0.176	1.000											
(6) Orders	−0.042	0.574	0.707	0.179	0.997	1.000										
(7) Platform_size	−0.039	0.121	0.031	−0.004	0.154	0.158	1.000									
(8) lnSEL	0.041	0.489	0.882	0.380	0.631	0.632	−0.003	1.000								
(9) lnReviews	−0.014	0.316	0.642	0.746	0.357	0.359	−0.002	0.789	1.000							
(10) lnDishes	0.036	0.221	0.466	0.849	0.246	0.248	−0.002	0.581	0.900	1.000						
(11) lnDish_Price	0.160	−0.094	−0.168	0.574	−0.096	−0.101	−0.011	−0.212	0.154	0.363	1.000					
(12) lnSales	−0.115	0.366	0.708	0.442	0.421	0.425	0.095	0.758	0.802	0.638	−0.065	1.000				
(13) lnCoupons	−0.132	0.392	0.682	0.366	0.480	0.489	0.298	0.696	0.705	0.552	−0.117	0.896	1.000			
(14) lnTenure	0.190	0.154	0.296	0.218	0.244	0.240	−0.023	0.394	0.371	0.323	−0.128	0.141	0.148	1.000		
(15) Male	−0.034	−0.139	−0.266	0.021	−163	−0.165	0.000	−0.316	−0.181	−0.182	0.243	−0.236	−0.196	−0.032	1.000	
(16) Age	−0.050	0.163	0.333	−0.330	0.173	0.175	0.002	0.449	0.193	0.029	−0.631	0.382	0.373	0.192	−0.495	1.000

hypothesized effects of this exogenous event on the behavioural responses of incumbents and new entrants.

During a limited period surrounding the platform policy change, unobserved factors are assumed to remain similar (Davis, 2008; Imbens and Lemieux, 2008). Thus, the data observation before the change would be a valid control group for causality identification (Imbens and Lemieux, 2008). In addition, as the location-based sorting policy change ranked incumbents, the effects on new entrants were not part of the platform's plan per se, which provides additional support for causal inference.

Using our rich dataset at the district level and the exogenous platform change, we develop a model of new seller entry (lnSEL_N). In this model, β represents the coefficients to be estimated and ε is the random error term, as follows:

$$\text{lnSEL\_N} = \beta X + \beta_1 * \text{R}P\text{R} + \beta_2 Rating * \text{R}P\text{R} + \varepsilon$$

where X is a matrix of control variables, and *RPR* and *Rating* are as described above.

The coefficients β_1 and β_2 will empirically test H1 and H2, respectively. Therefore, this model captures how the number of entrants (i.e., new sellers) is influenced by the platform design change (i.e., RPR) and the moderating role of the local sellers' quality. Moreover, we account for time trends in sellers, platform market growth, and saturation as our model controls for day-level time dummies T_t (which capture market evolution and time dynamics).

RESULTS

We present the results in Table III. The dependent variable *lnSEL_N* is the number of new sellers in a local market and the variables of interest are *RPR* (to measure the effect of the platform design change on new entry) and *RPR*Rating* (to measure the effect of highly rated incumbents on new entry after the platform design change). We present results with different models in columns 1–4. We also include time and market fixed effects to capture unobserved factors that do not change over time in the platform as a whole and in the market, respectively. The results from these models confirm our hypotheses.

In columns 1 and 2, we show the effect of *RPR* on new sellers while controlling for time, and time and market fixed effects; we find that *RPR* reduces the number of new sellers by 3.42 per cent ($\beta = -3.418$, *s.e.* (standard error) = 0.137) and 3.34 per cent ($\beta = -3.342$, *s.e.* = 0.143), respectively. In column 4, we include both *RPR* and the moderator (including both time and market fixed effects); we find that *RPR* reduces the number of new sellers by 3.25 per cent ($\beta = -3.245$, *s.e.* = 0.147) and the presence of high-quality sellers further reduces entry by 0.03 per cent ($\beta = -0.033$, *s.e.* = 0.012). These results are statistically significant and suggest that the negative effect is even stronger in markets with more highly rated incumbents. We also find that the market size is positive and statistically significant in all models.

Table III. Main results

	(1)	(2)	(3)	(4)
	lnSEL_N	lnSEL_N	lnSEL_N	lnSEL_N
Rating	−0.024	−0.006	−0.004	0.002
	(0.018)	(0.024)	(0.013)	(0.024)
Market_size	0.009***	0.008***	0.006***	0.009***
	(0.003)	(0.003)	(0.002)	(0.003)
Orders	−0.098	−0.065	−0.007	−0.093
	(0.113)	(0.118)	(0.097)	(0.118)
Platform_size	−0.002	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)
lnSEL	0.049***	−0.019	0.089***	−0.036
	(0.014)	(0.033)	(0.007)	(0.034)
lnReviews	0.04	0.057	−0.045***	0.07*
	(0.028)	(0.037)	(0.015)	(0.037)
lnDishes	−0.059	−0.055	0.024	−0.028
	(0.04)	(0.043)	(0.031)	(0.044)
lnDish_Price	0.146**	0.154**	0.183***	0.159**
	(0.058)	(0.063)	(0.05)	(0.063)
lnSales	−0.023*	−0.025*	−0.013	−0.027**
	(0.013)	(0.013)	(0.013)	(0.013)
lnCoupons	0.042*	0.044*	0.067***	0.044*
	(0.023)	(0.024)	(0.022)	(0.024)
lnTenure	−0.025	−0.092**	0.003	−0.117***
	(0.025)	(0.041)	(0.014)	(0.042)
Male	−0.037	−0.167	−0.056*	−0.286*
	(0.079)	(0.148)	(0.03)	(0.153)
Age	−0.002	−0.013*	−0.005***	−0.018**
	(0.003)	(0.007)	(0.002)	(0.007)
RPR	−3.418***	−3.342***	−3.377***	−3.245***
	(0.137)	(0.143)	(0.139)	(0.147)
RPR*Rating			−0.028***	−0.033***
			(0.011)	(0.012)
Constant	3.786***	4.724***	3.48***	4.998***
	(0.552)	(0.71)	(0.513)	(0.716)
Observations	4,273	4,273	4,273	4,273
R^2	0.61	0.61	0.60	0.61
Time FE	YES	YES	YES	YES
Market FE	NO	YES	NO	YES

Standard errors are in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

The results also show that RPR is the main driver of the reduction in entry rates and that local seller heterogeneity has a smaller effect. In other words, by reducing information asymmetry, the platform indirectly affects the entry of new sellers and thus provides some strategic advantage to incumbents. Although all markets exhibit lower entry because of the policy change, this effect is higher in those with already highly rated incumbents, which creates local variation in entry rates.

In summary, our results confirm that location-based sorting of sellers reduces the entry of new sellers. We also find that location-based sorting has a greater effect on entry to markets where there are more highly rated incumbent sellers and that this creates local variation in entry rates.

Sorting, Quality, and Variety

Our novel theoretical and empirical approach examines platform-level variation (i.e., *RPR*) and local market-level variation (i.e., local seller quality composition, *RPR*Rating*). In particular, we theoretically argue and empirically confirm that platforms' location-based sorting of sellers indirectly decreases the entry of new sellers and that local seller heterogeneity may further restrict this entry. This implies that a platform design change that decreases information asymmetry for buyers also reduces new entry when incumbent sellers have a strong competitive position.

However, it remains ambiguous whether a reduction in the number of new entrants affects product quality and variety. On the one hand, the indirect effect of sorting could benefit the platform: If the entry of low-quality sellers is restricted, the platform owners succeed in cultivating high-quality sellers, which increases platform value if product variety stays similar. This may occur because incumbents increase their efforts to improve their visibility and low-quality entrants are deterred from entry. On the other hand, if restricted entry increases quality but influences other measures of market structure (such as product variety), then entry regulation may have unintended negative consequences.

We expect that platform quality will increase but that sellers' incentives to introduce new products can either increase or decrease. Sellers will either increase their product offerings to compete in their local market by considering other incumbent sellers' behaviour, which may reconfirm their strategic position (Chevalier and Mayzlin, 2006), or they will reduce their variety, as the marketplace will exhibit lower entry rates and incumbents have a strategic advantage over potential entrants (Geroski, 1995).

Concerning the effect of the location-based sorting mechanism on quality, we calculate how the platform's policy change affected sellers' strategic decisions with respect to quality level (using seller-level data). In Table IV, panel A, we show, as expected, that overall quality increased after the design change. Specifically, the platform's overall average quality increased from 3.23 to 3.28 (an increase of 1.5 per cent). Both incumbents' and new entrants' (post-entry) average quality also increased from 3.23 to 3.28 (panel B and panel C, respectively). These calculations imply that incumbents increased their efforts and improved their quality after the policy change, while lower-quality entrants were indeed deterred from the market. This exercise is useful as it isolates how (incumbent and new) sellers respond to the policy change.

Table IV. Effect of platform change on quality

Platform Quality (as measured by ratings)	*Average*	*Standard Deviation*	*t-test*
A. Overall			
Before Platform Screening	3.2327	2.2843	138.81
After Platform Screening	3.2771	2.2667	
B. Incumbents			
Before Platform Screening	3.2342	2.2756	116.75
After Platform Screening	3.2749	2.2616	
C. Entrants			
Before Platform Screening	3.2286	2.3138	165.89
After Platform Screening	3.2793	2.3006	

To examine the effect of RPR on variety, we use the number of new dishes introduced in a given day compared to the previous day (*lnDish_N*) as a dependent variable. We present the results in Table V.

In column 2 of Table V, we see that the number of sellers increases new product variety ($\beta = 0.393$, *s.e.* $= 0.018$). Importantly, *RPR* reduces new variety in the platform by 2.75 per cent ($\beta = -2.751$, *s.e.* $= 0.165$) and the reduction is even larger when incumbent seller quality is higher ($\beta = -0.078$, *s.e.* $= 0.013$). These results imply that variety was reduced after the policy change and reduces even further when quality is higher.

But how did this policy change affect the platform's revenues? In Figure 1, we present the evolution of platform revenues during the period under study and, specifically, the evolution of revenues before and after the RPR implementation. We do not observe an effect on the overall total revenues although there was a slight decrease immediately after the policy change.

Overall, our results indicate that the location-based sorting mechanism increased overall quality but reduced variety in all markets. This effect on variety was greater in local markets with high-quality incumbents. Additionally, the revenues fell or remained constant after the policy change. These findings imply that although platforms can reduce information asymmetry and indirectly filter out low-quality sellers by implementing this platform design, this also indirectly decreases new product innovations across local markets because of the reduced efforts of high-quality incumbents.

Robustness Checks

We conducted various tests to examine the robustness of our results, which still hold. First, we divided our sample into a control group and a treatment group using each market's prior average rating. We used markets of sellers with high average ratings (above 2.7 out of 5) as a treatment group. Sellers in markets with high average quality should have greater incentive to improve on their place in the rankings compared to those in markets with low average quality or with only a few sellers. We present the

Table V. Quality and variety

	(1)	(2)
	lnDish_N	*lnDish_N*
Rating	0.056**	0.064**
	(0.025)	(0.025)
Market_size	−0.013***	−0.011***
	(0.003)	(0.003)
Orders	0.491***	0.393***
	(0.128)	(0.128)
Platform_size	0.002	0.002
	(0.002)	(0.002)
lnReviews	−0.079*	−0.052
	(0.04)	(0.04)
lnDishes	0.163***	0.227***
	(0.048)	(0.048)
lnDish_Price	0.328***	0.336***
	(0.07)	(0.069)
lnSales	0.039***	0.033**
	(0.015)	(0.015)
lnCoupons	0.118***	0.118***
	(0.026)	(0.026)
lnTenure	−0.337***	−0.363***
	(0.033)	(0.033)
Male	−1.21***	−1.409***
	(0.143)	(0.146)
Age	−0.04***	−0.049***
	(0.007)	(0.007)
lnSEL_N	0.398***	0.393***
	(0.018)	(0.018)
RPR	−2.922***	−2.751***
	(0.163)	(0.165)
Rating*RPR		−0.078***
		(0.013)
Constant	5.218***	5.568***
	(0.732)	(0.731)
Observations	4,273	4,273
R^2	0.92	0.93
Time FE	YES	YES
Market FE	YES	YES

Standard errors are in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

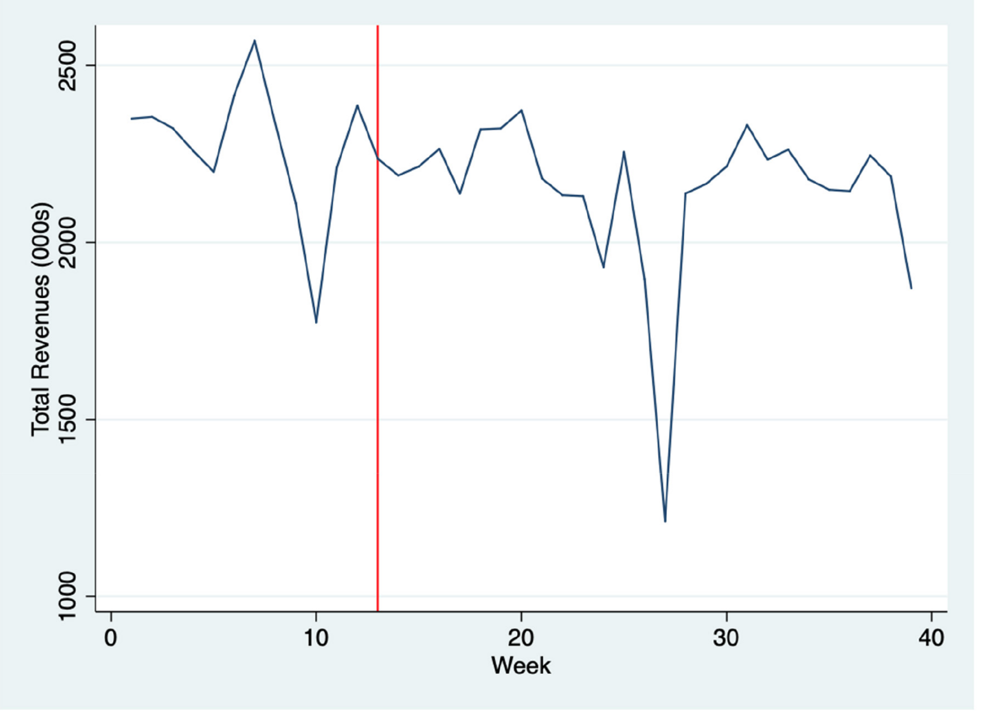

Figure 1. Platform revenues before and after the RPR [Colour figure can be viewed at wileyonlinelibrary.com]

results of this exercise in columns 1 and 2 of Table VI. Column 2, which includes time and market dummies, shows that the effect of the platform design change *RPR* and the interaction term *Treated***RPR* are still negative (−4.35 and −0.16, respectively) and statistically significant.

Next, we included additional dummies – market/time fixed effects – to examine whether unobserved factors that changed at the market level over time affect our main results. We present the results of this exercise in column 3. The estimates for *RPR* and *RPR***Rating* remain negative and statistically significant (−2.031 and −0.033, respectively).

DISCUSSION AND SUMMARY

This paper introduces a new dimension to the impact of location-based sorting on new entry, quality, and variety. We present evidence that platforms' sorting strategies should consider sellers' strategic decisions and local seller heterogeneity when designing the way in which users and incumbent sellers interact. We hypothesize that these sorting mechanisms may have the unintended consequence of strengthening incumbent sellers' strategic advantage and reducing the likelihood of new seller entry ex ante. We also find that, despite increasing overall quality, the reduction in information asymmetry may also indirectly reduce product variety by restricting new entry. This is particularly important

Table VI. Robustness checks

	(1)	(2)	(3)
	lnSEL_N	*lnDish_N*	*lnSEL_N*
Rating	−0.005	0.014	0.025
	(0.014)	(0.028)	(0.033)
Market_size	0.006***	−0.004	0.012***
	(0.002)	(0.003)	(0.004)
Orders	−0.008	0.224	−0.237
	(0.097)	(0.139)	(0.164)
Platform_size	−0.002	0.001	−0.005
	(0.002)	(0.002)	(0.008)
lnSEL	0.087***	0.145***	−0.093*
	(0.007)	(0.042)	(0.056)
lnReviews	−0.043***	−0.045	0.093*
	(0.015)	(0.044)	(0.052)
lnDishes	0.003	0.156***	−0.02
	(0.03)	(0.05)	(0.084)
lnDish_Price	0.173***	0.341***	0.184**
	(0.05)	(0.074)	(0.087)
lnSales	−0.011	0.024	−0.03
	(0.013)	(0.016)	(0.021)
lnCoupons	0.067***	0.134***	0.057
	(0.022)	(0.028)	(0.035)
lnTenure	0.008	−0.234***	−0.185***
	(0.015)	(0.049)	(0.067)
Male	−0.05*	−1.017***	−0.437**
	(0.03)	(0.18)	(0.211)
Age	−0.004**	−0.036***	−0.02*
	(0.002)	(0.008)	(0.011)
RPR	−3.423***	−4.352***	−2.031***
	(0.138)	(0.171)	(0.531)
Treated_RPR	−0.039*	−0.163***	
	(0.023)	(0.037)	
Rating_RPR			−0.033*
			(0.017)
Constant	3.489***	5.908***	5.273***
	(0.513)	(0.844)	(2.037)
Observations	4,273	4,273	4,273

(Continues)

Table VI. (Continued)

	(1)	*(2)*	*(3)*
	lnSEL_N	*lnDish_N*	*lnSEL_N*
R^2	0.60	0.92	0.79
Time FE	YES	YES	YES
Market FE	NO	YES	YES
Time/Market FE	NO	NO	YES

Standard errors are in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

for platform survival as buyers value both the number of sellers and variety (Boudreau, 2012).

Sharing economy platforms provide a unique setting to test our hypotheses. These online marketplaces affect how communities of users and sellers interact and exchange otherwise underutilized capital. The advantage of using this context (compared to more traditional platforms) is that it enables us to explore local market heterogeneity and sellers' overall strategic response. Therefore, it enables us to analyse how seller entry is influenced across local markets rather than at the aggregate platform level. Given that the sharing economy platform business model has emerged as one of the most important models in the modern digital economy, understanding the strategic behaviour of both incumbent and potential new sellers is pivotal.

Although previous papers have examined the role of platforms' actions in directly affecting quality or variety, we show that platforms may face indirect effects through the increased efforts of incumbents and deterred entry. Our study is the first to empirically uncover the indirect deterrent role of platform design in new seller entry and how it affects product quality and variety. Previous studies have separately focused on the implications of indirect network effects, platforms' decisions, and sellers' decisions (Boudreau, 2010; McIntyre and Srinivasan, 2017; Rochet and Tirole, 2003; Zhu and Iansiti, 2012) by concentrating on direct platform design changes that affect how sellers and buyers interact. Instead, our study shows that indirectly increasing the quality bar for new sellers directly affects variety in a local market through the mechanisms of new entry and entry deterrence. Additionally, we highlight the importance of local market heterogeneity when examining sharing economy platforms. Previous studies of platforms have examined the effect of policy changes at the aggregate level, have dismissed seller heterogeneity, and often have not considered the effects of local competition.

Our study has several managerial implications. Managers need to acknowledge that platform sorting design that focuses on incumbent sellers and buyers may have great consequences for product quality and variety. This implies that managers should consider the effects of policy design not only on incumbents but also on potential sellers. Therefore, managers may face an unintended trade-off between variety and quality when they design their systems.

Furthermore, in sharing economy platforms, seller entry depends on the interaction between platform design and local seller heterogeneity. In other words, entry does not depend only on platform sorting design but also on local market conditions such as incumbents' characteristics in a given market. Therefore, managers should consider how local seller heterogeneity may limit or enhance the effects of an aggregate platform design change.

This paper has several limitations. First, our results are time limited as we only have daily data for a short timeframe. Second, we focus on just one form of seller heterogeneity, i.e., quality composition. The nature of our data does not allow us to examine other forms of individual heterogeneity, such as seller investment or capacity constraints. Third, the platform design is exogenous in our context, so we do not know the reasons behind the platform owner's decision to introduce the sorting mechanism. It is likely that the platform owner may strategically choose when to introduce the sorting mechanism or to vary the change across local markets.

There are several possible avenues for future studies. Researchers could examine how a combination of individual recommendations and geographical sorting affect entry and variety in a platform. These algorithms learn from prior purchases and make personalized suggestions to buyers. In addition, future research could examine how other platform characteristics, such as the role of certifications for incumbents and entrants, affect new seller entry. These platform characteristics may be market driven rather than centrally planned by the platform owner and extend beyond consumer rating reviews to reduce information asymmetry and adverse selection. Finally, future studies could examine the indirect effects on offline firms. Platform-based markets often directly rival traditional offline industries (e.g., Uber/Lyft vs. the taxi industry, Airbnb vs. the hotel industry) and alter the competitive landscape.

ACKNOWLEDGMENTS

We thank the Editor and three anonymous referees for their constructive comments. Funding acknowledgement: This research is partially supported by the National Natural Science Foundation of China [Grants 72022007 and 71872080].

NOTE

[1] *New York Times* article about consumers focusing on the number of Uber/Lyft drivers in a specific geographical area: https://www.nytimes.com/2019/04/17/technology/personaltech/uber-vs-lyft.html.

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