Can Third-Party Sellers Benefit from a Platform's Entry to the Market?

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Due to the informational advantage of online marketplaces (i.e., platforms), it is a common belief that a platform's market entry will be detrimental to third-party sellers who sell similar products on the platform. To examine the validity of this belief, we conduct an exploratory analysis using the sales data for a single product category provided by JD.com for the month of March 2018. Our analysis reveals an unexpected result: Upon the platform's entry, third–party sellers who sell similar products can afford to charge a higher price, obtain a higher demand, and earn a higher profit.

To provide a plausible explanation for this unexpected exploratory result, we develop a duopoly model that incorporates the changing competitive dynamic before and after the platform's entry. Specifically, before entry, the platform earns a commission (based on the seller's revenue), while the seller sets its retail price as a monopoly. After entry, the platform earns a profit generated by its direct sales in addition to the commission from the seller. In addition, the seller and the platform operate in a duopoly, and engage in a sequential game. By examining the equilibrium outcomes associated with this sequential game, we identify conditions under which the platform's entry can create a win-win situation for both parties. Specifically, these conditions hold when the platform's market potential is moderate and when the platform's entry creates a sufficiently high spillover effect on the seller, providing a plausible explanation for our empirical finding that the seller can benefit from a platform's entry.

Key words: Online platform, platform entry, spillover, market potential

1. Introduction

Leveraging advanced information technology, many *online retailers* such as Amazon (which initially operated as an online book seller) and JD.com (which initially operated as an online electronic seller) have changed their initial business models to become *online platforms* by offering a platform for third-party merchants to sell their products online. Online platforms have fueled economic development (Chen et al. 2020) by creating value for all involved parties, as follows. First, online platforms enable the platform owner to offer a wide range of products by earning commissions (or selling service fees) from sellers without incurring the financial risks of owning the inventory of these products. Second, online platforms enable third-party sellers to sell online without losing control of pricing and inventory decisions. Third, online platforms reduce the "search cost" for customers who want to find good products at low prices. Because of these created value and the inherent cross-side network effect, many online platforms (e.g., Amazon, JD.com, Alibaba) have flourished at an unprecedented pace.

Conceptually speaking, Amazon and JD.com could have operated as "pure" platforms without selling similar products to compete with third-party sellers. However, they both decided to operate as "hybrid" platforms so that they would have the option to select some (similar or identical) products to sell on their own platform, resulting in direct competition with other sellers. By 2020, this hybrid platform business model had enabled Amazon's U.S. sales to increase by 44% to $318.41 billion, accounting for nearly 40% of the U.S. e-commerce market. More importantly, Amazon's sales generated from third-party sellers accounts for nearly 60% of Amazon's sales (Dai and Tang 2020). In a similar vein, China's Alibaba and JD.com respectively account for 55.9% and 16.7% of Chinese retail e-commerce sales.[1] Both Chinese firms operate as hybrid platforms by selling products that they themselves own and products owned by third-party sellers.[2]

An interesting question is: Why do Amazon and JD.com operate as hybrid platforms rather than pure platforms? Dryden et al. (2020a) argue that a key reason for a platform to sell its own products (in addition to products sold by third-party sellers) is to improve the quality of its offerings by adding some "missing varieties" to prevent customers from switching to other platforms or the third-party seller's own website.[3] Also, Zhu and Sun (2018) commented that JD.com sells certain products directly in addition to similar products sold by third-party sellers as a way to reduce counterfeits.

However, online platforms' active market entry has raised various fairness concerns. Because the platforms can observe sales transactions between all of their third-party sellers and customers, they have an informational advantage over their third-party sellers. In addition, platforms design the user interface and can use search engine optimization to favor their own products. Thus, there are concerns that online platforms' market entry to compete with existing sellers can endanger the long-term resilience of retail marketing (Khan 2019, Zhu 2019). For example, the European Union has investigated whether Amazon "unfairly uses the data of third-party complementors on

[1] `https://www.emarketer.com/content/alibaba-jd-com-lead-in-china-but-a-few-others-are-making-dents-too`

[2] Alibaba is more reliant on marketplace sales, with direct sales contributing to about 27% of Alibaba's revenue as of June 2021 (see `https://www.alibabagroup.com/en/news/press_pdf/p210803.pdf`). In contrast, JD.com is more reliant on direct sales, which account for more than 80% of its revenue (see `https://ir.jd.com/static-files/fc93d5dd-9437-4141-9191-f960ba46874b`).

[3] Some third-party sellers use hybrid platforms as a marketing tool to advertise their products or brands with the hope of directing traffic to their own websites.

its platform to decide which markets to enter" (Wen and Zhu 2019). Similarly, the U.S. Senate held a hearing about Amazon when it was accused of unfair practice in selling similar products to compete,[4] and the Chinese government issued the "Antitrust Guidelines for the Platform Economy Industry" in February 2021 to regulate unfair practices of e-commerce platforms.[5]

Putting fairness concerns aside, researchers have found mixed results regarding the impact of a platform's market entry. Based on data collected in the US, Zhu and Liu (2018) find that third-party sellers tend to respond to a platform's entry into the market by reducing the number of products they sell on the platform. However, based on data collected in France and Germany, Dryden et al. (2020b) find an opposite result. Zhu (2019) describes these mixed results regarding platforms' market entry and suggests that more research is needed to examine third-party sellers' response to platforms' market entry. Zhu (2019)'s suggestion motivates us to examine the following research questions:

1. What types of products do platforms choose when entering the market?
2. How do incumbent sellers respond to the platform's market entry (in terms of their selling prices)?
3. How does the market respond to the platform's entry (in terms of the market potentials)?
4. Can sellers benefit from the platform's entry?

Due to the underlying competition, it is common to expect that the third-party sellers' sales should decrease upon the platform's entry. Also, one would expect the third-party sellers to respond to the platform's entry by reducing their selling prices in order to compete for sales. To examine the validity of the common belief that a platform's entry will hurt an existing third-party seller's sales by forcing the seller to lower its selling price, we first conduct an exploratory analysis using sales data for a single product category provided by JD.com for the month of March 2018. Our data analysis reveals that the platform tends to enter the market by "cherry picking" cheaper and popular items. This result is expected, but we also find an unexpected empirical finding: Upon the platform's entry, third-party sellers who sell similar products tend to respond by selling at a higher price (a 1.2% increase), and even with a higher selling price, the sellers enjoy a higher sales volume (a 4.8% increase). This unexpected result is certainly counterintuitive and deserves further examination.

Because of the limitation of the sales data available to us, our exploratory analysis stops short of establishing causality. Therefore, we develop an analytical model in order to identity a plausible explanation for this surprising result. Specifically, we develop a duopoly model that involves an

[4] See: `https://www.washingtonpost.com/technology/2020/07/29/bezos-testimony-data-antitrust/`.

[5] See: `http://gkml.samr.gov.cn/nsjg/fldj/202102/t20210207_325967.html`.

incumbent third-party seller who pays a sales-based commission to sell a product on a hybrid platform, while the platform has the option of entering the market to earn additional profits by selling a similar product on its own marketplace as a way to compete with the incumbent seller. In this duopoly model, the nature of the competition before and after the platform's entry is different.

Specifically, before entry, the seller operates as a monopoly: the platform earns a commission (based on the seller's revenue) while the seller sets the retail price. However, after entry, the platform earns a profit generated by its direct sales in addition to the commission obtained from the seller. Also, after entry, the seller and the platform operate in a duopoly, and engage in a sequential game as follows. The platform acts as leader who sets its market entry price. Then, upon observing the platform's market entry price, the seller sets its own selling price.

We analyze this sequential game via backward induction and determine various equilibrium outcomes. Our analysis of the equilibrium outcomes reveals several insights. First, we identify the conditions under which the platform will choose to enter to increase its profit. Specifically, we find that the platform will certainly avoid entering markets with low market potential, but it will also intentionally avoid markets that can hurt its commission revenue despite their high market potential. Second, we find that when the platform's market potential is moderate and when the seller's "spillover effect" induced by the platform's entry (Handarkho 2020, He et al. 2020) is sufficiently high, the seller can benefit from the platform's entry, charging a higher price, obtaining a higher demand, and earning a higher profit. However, in the absence of a positive spillover effect, the seller is always worse off following the platform's entry.

This paper contributes to the ongoing debate regarding the impact of a retail platform's market entry on third-party sellers and customers. In contrast to the popular conceptions (e.g., public hearings), we show analytically that, despite competition, the platform's entry can benefit the seller under certain market conditions (i.e., when the platform's market potential is moderate and when the seller's spillover effect (induced by the entry) is sufficiently high. These analytical conditions provide a plausible explanation of our empirical findings. In particular, our empirical observation of an increase in sellers' prices in response to JD.com's market entry can be explained by the presence of a positive spillover effect, and both the platform (which earns more sales commissions in addition to its profit generated from direct sales) and the sellers (who benefit from the positive spillover) benefit from the market entry.

The rest of this paper proceeds as follows. §2 examines the related literature and highlights our study's contributions. §3 describes our data, and §4 conducts exploratory data analyses. Motivated by the results in §4, §5 introduces a stylized duopoly model and analyzes the equilibrium results, and provides an integrated discussion of the empirical observations and the analytical model results. We conclude in §6 with a summary of our findings and suggestions for future research.

2. Relevant Literature

Our paper is related to two emerging research streams: the business model of online retail platforms, and the implications of platform market entry. Various researchers have examined the business models of different online retail platforms. Hagiu and Wright (2015) examine the trade-offs between the online retailer model through direct sales and the online (pure) platform model that earns commissions through the sales of third-party sellers; they consider several factors, including spillover, information, and cost advantage. Tian et al. (2018) examine the strategic choice between online retailing, a pure platform, and a hybrid platform, while Abhishek et al. (2016) examine the conditions under which the pure platform model outperforms the online retailing model. Hagiu et al. (2022) examine the implication of the dual mode in which the platform operates both as a marketplace and as a seller, and the welfare effects of regulations. Some researchers have also investigated the value created by online platforms. Specifically, an online platform can increase consumer utility when individual sellers are not too powerful (Mantin et al. 2014) or when the platform charges the seller a sales-based commission (instead of a fixed fee) (Wang and Wright 2017, 2018).

There is a vast empirical literature that examines the impact of a platform's entry; here the reader is referred to Zhu (2019) for a comprehensive review that examines the platform's market entry for social media platforms, video game platforms, software platforms, and retail platforms. Various researchers have investigated Amazon's market entry decisions and their impact on third-party sellers. For example, Zhu and Liu (2018) report that Amazon tends to enter product spaces that are more popular (i.e., higher sales and higher customer ratings). Regarding incumbent sellers' response, Zhu and Liu (2018) find that, upon Amazon's entry, sellers may reduce their product offerings as they are "discouraged from growing their businesses on the platform."

In addition to the empirical research, a strand of analytical research examines the implications of a platform's market entry. For example, Jiang et al. (2011) show analytically that a platform's market entry can induce a seller to disguise the high demand for its product by dampening sales via reductions in its service level. Hagiu and Spulber (2013) find that by introducing first-party content alongside third-party content, a platform can mitigate the coordination problem in user participation. Hagiu et al. (2022) find that the competitive pressure associated with a platform offering similar products lowers the third-party seller's price in equilibrium.

In light of this brief review of the previous literature, we see the contributions of this paper relative to the extant literature to be two-fold. First, the individual customer purchase data allow us to demonstrate consumers' inherent preferences for products carried by the platform, providing a foundation for the modeling choice. Second, we complement the analytical literature on platform entry by investigating the platform's market entry conditions, and identifying conditions under which the incumbent seller counter-intuitively increases price upon the platform's entry.

3. Data Description and Preparation

We conduct an exploratory analysis to gain a better understanding of the platform's market entry decisions, the incumbent sellers' response, and the market's response. Here our goal is to examine the three basic questions articulated in §1: (1) What types of products do platforms choose when entering the market? (2) How do incumbent third-party sellers respond to the platform's market entry? (3) How does the market respond to the platform's entry?

We first describe our data provided by JD.com. Then, in §4, we present our exploratory analysis to show that: (1) JD.com tends to cherry pick popular and cheaper products for entering the market; (2) incumbent sellers tend to respond to JD.com's market entry by increasing their selling prices; and (3) the market potential for sellers' products tends to increase upon JD.com's entry.

3.1. Data Source

We employ the data supplied by JD.com for the 2020 MSOM Data Driven Research Challenge.[6] To avoid repetition, we refer the reader to the detailed description of the data in Shen et al. (2020). Briefly, the database includes customers' ordering activities associated with all stock-keeping units (SKUs) within a *single anonymized consumables product category* for the month of March 2018. However, the database does not contain information about customers who did not place an order after browsing. Each SKU is associated with a brand ID along with two key attributes: attribute 1 takes a value between 1 and 4, and attribute 2 takes a value between 30 and 100. For each attribute, a higher value indicates better performance with respect to a certain functionality (e.g., longer battery life, higher screen resolution). For each product, we do not observe the seller ID, but there is a field indicating whether the product is owned by a third-party seller or by JD.com. Specifically, the SKU IDs are seller-specific but not product-specific, so that identical products sold by different sellers are associated with different SKU IDs. Hence, the data have two limitations: (a) we can identify the brand for each SKU, but we cannot identify the third-party seller who owns that SKU; and (b) we know the attribute value and the brand of each SKU, but we cannot identify whether two different SKUs that belong to the same brand are indeed the same product.

There were 31,868 SKUs in the database, of which 1,167 were sold by JD.com and the rest by third-party sellers.[7] Also, there were 457,298 consumers who purchased at least one product in the product category during March 2018, and these orders include 9,159 unique SKUs. Out of these 9,159 SKUs, 5,372 SKUs have complete information for attributes 1 and 2. For each order, we observe the time of the order, the order quantity, the original list price, and the final price. The

[6] Details about this challenge competition are available at https://connect.informs.org/msom/events/datadriven2020

[7] Among the 31,868 SKUs, we have complete information about attributes 1 and 2 for 13,725 SKUs (of which 422 were carried by JD.com), and 357,820 orders involve at least one of these 13,725 SKUs.

final price for an SKU can vary among purchases due to various discounts and promotions. Finally, we observe each customer's "click history" for all products in the product category. These click histories enable us to construct a choice set for each consumer during each "purchase occasion." We use these choice sets for different customers when we estimate our consumer choice model in §4.1.

3.2. Data Preparation

In order to characterize the market, we construct an SKU-day panel from the customer order data.

3.2.1. Price, Discount Rate, and Lead Time.

To facilitate our data analysis, we define two price variables: the *original unit price* and the *final unit price*, and we measure the "discount rate" as the difference between the original and final unit prices *divided by* the original unit price. We define *lead time* as the difference between the order delivery date and the order placement date.

For a given SKU and a given day, the (original and final) price, discount rate, and lead time can vary across orders because consumers may use different discount coupons (which affect the final price and the discount rate), and different consumers may be located in different geographical regions (which affects the lead time). Using the raw data associated with the 457,298 consumers who purchased at least one of the 31,868 SKUs in the product category, as explained above, we can measure these variables at the *SKU-day level*.[8]

Table 1 provides the summary statistics based on 9,159 unique SKUs that were ordered at least once during the month of March 2018, as explained in §3.1. The average daily sales of these 9,159 SKUs was 72.51 units, with a standard deviation of 560.65 units. In addition, the average final daily price for an SKU was 121.29 Yuan, with a standard deviation of 313.57 Yuan. Note that there are four binary variables for attribute 1 and eight binary variables for attribute 2, each corresponding

[8] For each SKU that appears in multiple orders on a given day, we use the average original unit price as the original unit price and the average final unit price as the final unit price at the SKU-day level. Also, if an SKU is not ordered by any customer on a particular day, we use the previous day's orders to infer the SKU's original and final unit prices. If there is no order for an SKU for the first several days after the day on which the data begin, we use orders from the first day on which orders for that SKU are observed to infer the original and final unit prices for earlier days. Then we compute the SKU-day–level discount rate using the SKU-day–level prices computed in steps 1 and 2.

Because each order may contain multiple SKUs and each order has a "designated" lead time for the entire order (defined as the time between the actual delivery time and the time of order), we compute the average lead time for each SKU as follows. (a) For each SKU that was included in at least one order on a given day, we compute the lead time for the SKU as the average lead time of all orders that involve that SKU on that day. (b) For SKUs that were not ordered during the data period, we use the 95th-percentile lead time of all orders in the data as the lead time. While price and discount rate are observable by customers during each choice occasion, the lead time for each SKU is not directly observable before the order is fulfilled. Although JD.com provides an expected delivery time, this information is not available for items in the choice set that were not purchased. Also, the expected delivery time is often different from the actual delivery time. To overcome this limitation, we use the "average lead time" as a proxy, and we assume consumers form rational expectations about the lead time. We acknowledge potential measurement errors in lead time.

to one level of the attribute. As mentioned in §3.1., 5,372 of the SKUs have complete attribute information. Table A-1 in the Appendix presents the correlation matrix for these variables.

Table 1 Summary Statistics for the Order Data (aggregated at the SKU level).

Variables	Number of Observations	Mean	Std.Dev.
Total sales units	9,159 (# of SKUs)	72.51	560.65
If sold by JD.com	9,159	0.04	0.19
Average final price (in Yuan)	9,159	121.29	313.57
Average lead time (in days)	1,784 (# of SKUs with lead time info.)	2.96	1.69
Average discount rate	8,814	0.15	0.20
Attribute 1=1 (binary variables)	5,372 (# of SKUs with attribute info.)	0.04	0.20
Attribute 1=2	5,372	0.16	0.37
Attribute 1=3	5,372	0.52	0.50
Attribute 1=4	5,372	0.28	0.45
Attribute 2=30 (binary variables)	5,372	0.01	0.10
Attribute 2=40	5,372	0.02	0.15
Attribute 2=50	5,372	0.05	0.22
Attribute 2=60	5,372	0.29	0.45
Attribute 2=70	5,372	0.05	0.21
Attribute 2=80	5,372	0.02	0.15
Attribute 2=90	5,372	0.01	0.10
Attribute 2=100	5,372	0.55	0.50

Note: We measure each variable for each SKU. Each observation is associated with an SKU that has been ordered by at least one customer during the month of March 2018. There are fewer observations for lead times, discount rates, and attributes due to missing values.

3.2.2. Product Space Definition.

Because our data are based on a single product category, it is not appropriate to view a category as a market. To overcome this shortcoming, we adopt the "product space" concept introduced by Zhu and Liu (2018). Specifically, Zhu and Liu (2018) first define "product spaces" as unique products. Then they characterize "product space entries" based on the products that Amazon did not offer in the first round of their data collection but started offering in the second round. However, our data are based on SKU IDs, as explained in §3.1. Specifically, SKU IDs are seller-specific (i.e., sold by JD.com or sold by different third-party sellers), so that identical products sold by different sellers are associated with different SKU IDs.

Because of this limitation of our data and because all SKUs belong to the same product category, we define a "product space" as a collection of products that have the *same brand ID* and the *same attribute values* associated with attribute 1 and attribute 2. Based on this definition, we established 2,293 *unique* product spaces in our data set.[9] Because we know whether an SKU was sold by

[9] Although we are unable to provide direct evidence on the similarity between products within the same product space, we find that SKUs within the same product space are "relatively more similar" than those SKUs belonging to different product spaces. To elaborate, we first compute the mean and standard deviation of prices for products *within* each product space based on data for the first day of the observation period. Then we compute the standard

JD.com and when the SKU was introduced, we can infer JD.com's product space entry as when JD.com began to sell a product during the month of March 2018. Of the 2,293 product spaces, our database indicates that JD.com entered 61 product spaces before March 2018 by carrying some SKUs that belong to those 2,293 product spaces. During March 2018, JD.com entered an additional 18 product spaces that had previously been sold primarily by third-party sellers. Therefore, during March, 2018, JD.com entered 0.8% = 18/(2293 – 61) of the product spaces that it had not entered earlier. Entering 0.8% of the untapped product spaces in a given month is consistent with Zhu and Liu (2018)'s finding. Specifically, based on observations over a 10-month period, Zhu and Liu (2018) find that the percentage of Amazon's product market entries in different subcategories ranged from 0% to 7.34%.

4. Exploratory Data Analysis of a Platform's Market Entry

Using the variables summarized in Table 1, we now perform three different exploratory analyses to examine the questions asked in §3. First, we develop a consumer choice model to examine consumer preferences between a product carried by JD.com versus a similar product carried by third-party sellers within the same "product space," as defined earlier. Then we examine the characteristics of the product space that JD.com tends to choose when entering the market. Finally, we present a difference-in-differences (DID) regression model to examine the sellers' responses to JD.com's market entry (in terms of prices) and the market's responses to JD.com's market entry (in terms of sales). Due to the limitations of the sales data, these analyses are descriptive in nature and are not intended to identify causality.

4.1. Consumer Choice Model: Consumer Preferences

In this section, we present a consumer choice model to assess consumer preferences in terms of product attributes and the actual seller (JD.com versus third-party sellers). Our choice model is based on different "choice occasions" that are defined by consumer product searches (measured by clicks) and the final product choice when a consumer places an order. For each choice occasion, we formulate customers' choice sets based on their click history over a 24-hour time window prior to placing the order. That is, the choice set for a customer includes the set of products that the consumer clicked at least once during this time window. The data include 236,394 orders, of which 53.5% involve purchases of products sold by JD.com. The choice sets associated with these orders include 972 brands and 8,149 products, within which 47.1% are sold by JD.com.

deviation of the product space-level mean price. The "within-product space" standard deviation of price is 44.2, which is much lower than the "cross-product space" standard deviation of mean price which is 195. Also, the within- and cross-product space standard deviations of sales quantity are respectively 8.3 and 29.5. These observations suggest higher similarity of SKUs within a product space than across product spaces, supporting the validity of the definition of product space.

Our consumer choice model is based on the following indirect consumer utility function:

$$u_{ij} = X_{ij}\beta + \alpha p_{ij} + \varepsilon_{ij}, \tag{1}$$

where i is a choice occasion (or a consumer)[10] and j denotes an SKU in the choice set during choice occasion i. The term X_{ij} is a vector of product characteristics, as shown in Table 1, including attribute 1, attribute 2, brand,[11] lead time, discount rate, and a binary variable that equals 1 when the product is sold by JD.com, p_{ij} is the final unit price associated with product j on choice occasion i, and ε_{ij} is the error term. Price and the discount rate of the "chosen" SKU correspond to the observed price and discount rate in the order. Lead time of all SKUs, as well as price and discount rate of those "non-chosen" SKUs in the choice set, are operationalized with the approach as described in §3.2.1. We only consider choice occasions that lead to successful transactions. In other words, we exclude those occasions when consumer clicks do not result in purchases. Therefore, we do not include the outside good option (representing the non-purchase) in the model. We do not constrain the signs of any parameters.

Assuming that ε_{ij} follows the Type I extreme value distribution, it is well known that the probability of having consumer i choose SKU j can be expressed as:

$$P_{ij} = \frac{\exp(X_{ij}\beta + \alpha p_{ij})}{\sum_{j' \in A_i} \exp(X_{ij'}\beta + \alpha p_{ij'})}, \tag{2}$$

where A_i is the choice set associated with choice occasion i. Using these probabilities P_{ij}, we can estimate the parameters of our model by maximizing the following likelihood function:

$$\max_{\alpha,\beta} \prod_i \prod_j P_{ij}^{y_{ij}} (1 - P_{ij})^{1-y_{ij}},$$

where y_{ij} is an indicator variable for whether (or not) product j was purchased on choice occasion i.

Table 2 summarizes the estimated values of the model parameters associated with the consumer choice model, as given in Equation (1). Both Columns (1) and (2) control for the final unit price, the discount rate, the lead time for each SKU, and the fixed effect of the top 20 brands. However, Column (1) does not control for the attribute dummy variables, while Column (2) does control for the attribute dummies. Because attribute variables are missing for many of the SKUs, the number of observations is much smaller in Column (2) than in Column (1).[12] In addition, because few

[10] This is because 94.2% of the consumers placed only one order in March 2018; hence, we do not treat the data as panel data.

[11] We use 20 dummy variables to control for the top 20 brands, which account for 69% of both the sales quantity and the total revenue among more than 1,400 brands.

[12] Because the models presented in Columns (1) and (2) have different numbers of observations, comparisons of log likelihood and AIC are not meaningful. For this reason, these two measures are omitted.

Table 2 **Estimation Results for Consumer Utility.**

Variables	(1)	(2)
If carried by JD.com	0.152***	0.189***
	(0.011)	(0.013)
Attribute 1: Level 2		0.190***
		(0.027)
Attribute 1: Level 3		0.124***
		(0.026)
Attribute 1: Level 4		–0.092**
		(0.028)
Attribute 2: Level 40		–0.302***
		(0.040)
Attribute 2: Level 50		0.003
		(0.035)
Attribute 2: Level 60		0.094***
		(0.033)
Attribute 2: Level 70		0.014
		(0.035)
Attribute 2: Level 80		0.022
		(0.036)
Attribute 2: Level 90		0.376***
		(0.039)
Attribute 2: Level 100		0.297***
		(0.034)
Final unit price	–0.005***	–0.005***
	(0.001)	(0.000)
Discount rate	0.612***	0.721***
	(0.015)	(0.018)
Lead time	–0.062***	–0.024***
	(0.004)	(0.005)
Brand fixed effect	Yes	Yes
Observations	1,221,801	891,584
Number of choices	236,394	190,301

Note: Standard errors are given in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

SKUs have levels 40, 50, 70, 80, and 90 of Attribute 2 as shown in Table 1, estimates on these levels rely on fewer observations and may therefore be less robust than estimates on levels 60 and 100 which rely on more observations.

Observe from Table 2 that, all else being equal, consumers preferred products that were offered by JD.com, products that were cheaper and were discounted more heavily, and products with a faster delivery. These results have the following implications. In view of the consumers' preference for products sold by JD.com, there is an incentive for JD.com to enter the market by choosing cheaper SKUs (i.e., products that are sold by third-party sellers at lower prices) to compete with the incumbent third-party sellers.[13] We next investigate whether JD.com did indeed adopt this strategy when entering the market.

4.2. Platforms' Market Entry: Product Choice

In this section, we characterize the product spaces selected by JD.com when entering the market. Specifically, we first compute, at the product space level, the average final unit price (set by third party sellers), the average number of units sold (by third party sellers), the average revenue (obtained by third party sellers), and the number of unique SKUs. Then we divide the product spaces into three distinct groups according to JD.com's market entry strategy: (i) product spaces that JD.com had *not entered* (by the end of March, 2018); (ii) product spaces that JD.com *entered during March, 2018*; and (iii) product spaces that JD.com *entered before March, 2018*. Those three groups are associated with 1,271, 18, and 61 product spaces, respectively. Finally, we compute the average values of different measures for each of these product space groups in Table 3.

Table 3 **Characteristics of SKUs Sold by Third-party Sellers in the Different Product Space Groups (grouped by JD.com's entry decisions).**

Group \ *Variable*	Avg Final Price (Yuan)	Avg Units Sold	Avg Revenue (Yuan)	Avg #SKUs
JD.com had not entered	116.8	119.4	7,125.6	3.4
JD.com entered during March 2018)	75.2	707.3	46,381.2	13.3
JD.com entered before March 2018	76.0	1147.3	59,012.8	15.6

By comparing the top row with the middle and bottom rows in Table 3, we can draw the following conclusions. First, JD.com entered the market before March 2018 by choosing products that were relatively cheap (priced by third-party sellers at 76 Yuan on average during March) compared to the group of product spaces that JD.com had not entered by the end of March 2018, and relatively popular (with 1147.3 units sold on average by third-party sellers during March), generating high revenue for third-party sellers during March. The same pattern can be observed for those products that JD.com selected for entering the market in March 2018 (middle row). These observations imply that JD.com tends to cherry pick cheaper and popular items when choosing which markets to enter. This finding is consistent with results obtained by Zhu and Liu (2018), who claim that Amazon tends to enter markets that are popular, with high customer ratings.

Knowing that JD.com tends to enter the market by cherry picking products that are cheap and popular, how did the third-party sellers who sold similar products respond to JD.com's entry? Will they declare a price war by lowering their prices? What was the market response to JD.com? Did JD.com's entry affect the third-party sellers' sales negatively? We examine these issues next.

[13] By virtue of its ability to offer a deeper discount and shorter lead time, JD.com can increase its profit margin significantly.

4.3. Sellers' Price Response and Market Sales Response to the Platform's Market Entry

To examine the incumbent third-party sellers' response and the market sales response to JD.com's market entry, we now estimate a difference-in-differences (DID) regression model using the SKU-day–level data as described in §3.2.1. The data are based on a balanced panel including 8,858 third-party SKUs in 2,288 product spaces. Among these SKUs, 239 SKUs are in the 18 product spaces that JD.com entered during the data period. For these 239 SKUs, 2,680 observations occurred before entry, and 4,729 observations occurred after entry.

The DID regression model is specified as follows:

$$ln\,(y_{ijt}) = \beta \times Enter_j \times AfterEnter_{jt} + \delta_{ij} + \eta_t + \epsilon_{ijt}, \tag{3}$$

where i denotes an SKU (sold by third-party sellers) that belongs to product space j, j denotes a product space, and t denotes a day during March 2018. Here, the generic dependent variable y_{ijt} can be: (1) the logarithm of the final unit price (in Yuan) of SKU i in product space j on day t, or (2) the logarithm of the total sales quantity of SKU i in product space j on day t. The independent variables are as follows. $Enter_j$ is an indicator variable representing whether or not JD.com entered product space j in March 2018. $AfterEnter_{jt}$ is an indicator variable indicating whether or not day t occurs *after* JD.com's market entry date associated with product space j. Thus the interaction term $Enter_j \times AfterEnter_{jt}$ is the DID variable of interest, and parameter β is the parameter of interest. The parameter δ_{ij} captures the fixed effect of SKU i belonging to product space j. This fixed effect captures unobservable time-invariant factors that are specific to the SKU. The parameter η_t captures the fixed effect of day t. Finally, ϵ_{ijt} is an idiosyncratic error term.

As shown in Table 4, we ran the above regression model under three settings. In Column (1), ln(final unit price) for a third-party SKU is the dependent variable. In Column (2), ln(daily sales quantity) for a third-party SKU is the dependent variable,[14] followed by an augmentation that includes ln(final unit price) as an additional independent variable in Column (3).

Table 4 reveals two unexpected results. First, upon JD.com's market entry in March, one would expect that third-party sellers who sold similar SKUs within the same product space would reduce their selling prices to compete. However, Column (1) shows the opposite: Third-party sellers increased their prices for similar SKUs by 0.88% upon JD.com's entry.

Second, as JD.com entered the market in March, one would expect the third-party sellers' sales to be decimated, especially when consumers preferred products carried by JD.com, as shown in

[14] Due to the log function, we use ln(total unit sales + 1) to ensure that the value is bounded when sales equal zero.

Table 4 **Seller Price Response and Market Sales Response to JD.com's Product Space Entry.**

Variables	(1) ln (Final unit price)	(2) ln (Total unit sales+1)	(3) ln (Total unit sales+1)
Entry*After entry	0.0088***	0.0111	0.0335***
	(0.002)	(0.012)	(0.011)
ln(Final unit price)			–0.5125***
			(0.009)
SKU FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	262,263	274,598	262,263
Number of SKUs	8,531	8,858	8,531
Adj. R-Squared	0.988	0.611	0.611

Note: Standard errors are given in parentheses; *** $p < 0.01$. The dependent variable is the logarithm of the SKU's price (Column 1) or sales quantity (Columns 2 and 3) on a given day. The independent variable is whether JD.com entered the product space of the SKU and that the day is after JD.com's entry. There are more SKUs in Column (2) than in Columns (1) and (3) because the final unit price is missing for 327 of the 8,858 SKUs.

our consumer choice model in §4.1. However, Column (2) shows that JD.com's entry does not significantly affect sales, and when controlling for the final unit price, Column (3) shows the daily unit sales of third-party sellers' SKUs increased by 3.35% upon JD.com's entry. The results associated with Column (3) imply that JD.com's market entry created positive "spillover" sales effects: JD.com's entry generated sales for itself, but it also increased sales for third-party sellers. This positive spillover effect can be explained as follows. For each of the 18 product spaces that JD.com entered in March, its entry improved market awareness about all of the SKUs within that product space. Additionally, JD.com's entry could be seen as an endorsement of all SKUs within that product space because they share the same brand and the same attribute levels. Therefore, even though consumers may prefer the SKU carried by JD.com, consumers may also prefer similar SKUs carried by third-party sellers due to attributes other than attributes 1 and 2 (e.g., color). For this reason, JD.com's market entry could boost the market potentials for the third-party sellers as well.

We emphasize that the results generated from our regression models are exploratory and descriptive. We do not claim any causal relationships because there are endogeneity issues for the following reasons. First, as shown in §4.2, JD.com engaged in cherry-picking behavior when selecting its products for market entry, so the product selections for market entry may not be random. Second, as our data cover only the transactions within a single month, the time frame to evaluate the impact of the entry is less than a month, which might limit our ability to fully assess the actual or long-term impact of JD.com's entry. Given this data limitation, we were unable to address the endogeneity issues with causal inference methods by identifying events that took place in March 2018 to construct instrumental variables or by leveraging JD.com's market entry policy. Nevertheless, the results presented in Table 4 are intriguing: Why would incumbent sellers increase their selling price upon JD.com's market entry? How could sellers sell more upon JD.com's entry? What are the platform's entry conditions that can enable sellers to afford to charge a higher price and obtain a higher demand? We examine these questions by constructing a parsimonious model to see if there is a plausible explanation for these unexpected results as shown in Table 4 in the next section.

5. An Analytical Model: Platform's Entry and Seller's Response

Putting the causality issues aside, our regression models presented in §4.3 generated two unexpected results: (a) sellers responded to JD.com's market entry by increasing their prices; and (b) the market responded to JD.com's entry with higher market potentials for the sellers due to the "positive spillover" effect discussed earlier. Considering the positive spillover effect created by the platform's market entry, we now present a parsimonious and stylized model to examine a key question analytically: Is there a plausible and rational explanation for the seller's price increase and demand increase as a response to the platform's market entry?

To abstract away various issues (e.g., number of sellers, number of products, and so forth) so that we can focus primarily on the platform's market entry and the sellers' response, we present a duopoly model to capture the underlying competition between a seller and a platform. Even before considering the potential entry, the platform has established the commission rate ϕ way in advance, and this rate will not change, regardless of the platform's entry. Hence, we treat ϕ as a parameter and not a decision variable.[15]

5.1. Consumer Utility and Demand Functions

We use a unified consumer utility function to generate consistent demand functions for two settings: (N) no platform entry; and (E) with platform entry. This consumer utility model is based on an approach established in the economics literature (e.g., Anderson et al. 1992, Dixit 1979, Singh and Vives 1984, Gui et al. 2019).

Setting (N): No Platform Entry. Without platform entry, the monopolistic seller sets his selling price p_S to maximize his net profit, while the platform collects her commission based on the seller's revenue. And consumers purchasing d_S from the seller in total will receive a utility:

$$u\left(d_S\right) = kd_S - \left(\frac{d_S^2}{2}\right) - p_S d_S, \tag{4}$$

where p_S is the seller's price, and k is the "market potential" for the seller created by the product's inherent quality and the seller's reputation. By differentiating the utility with respect to d_S, the demand for the monopolistic seller is:

$$d_S = k - p_S, \tag{5}$$

[15] This setting captures the actual practice of JD.com and Amazon, who pre-announce their commission rates on their websites before any market entry.

which is the standard demand function that is linearly decreasing in price.

Setting (E): With Platform Entry. When the platform enters the market selling a similar product (to compete with the seller) in a certain product category, it enhances the visibility and creates awareness (Handarkho 2020). This heightened awareness can drive more consumers to learn more about this product, which can drive up the demand for the platform and the seller (Kang 2017). Also, because of the platform's *cherry picking* behavior (Zhu and Liu 2018) as exhibited in Table 3 of §4.2, consumers know that the platform will only enter the market by selling popular and good quality products. As such, the platform's entry also sends a signal to consumers that the product selected by the platform has great value and good quality (Zeng and Dong 2021), which, in turn, can attract more product demand for both parties. More importantly, Li and Agarwal (2017) show that, the platform's entry can drive up the demand for the platform first, and then this increased demand can "spillover" to the seller selling a similar product. We also find the existence of this spillover effect created by the platform's entry as discussed in Table 4 of §4.3.

To capture the platform's organic demand following its entry, the seller's spillover effect associated with the platform's entry, and the price competition triggered by the platform's entry, we model the corresponding consumer utility for purchasing d_S and d_P respectively from the seller and the platform in setting (E) as follows:

$$u\left(d_S, d_P\right) = \beta k d_S + \alpha k d_P - \left(\frac{d_S^2 + 2\gamma d_S d_P + d_P^2}{2}\right) - p_S d_S - p_P d_P, \tag{6}$$

where p_S and p_P are the selling prices specified by the seller and the platform, respectively.

Observe from (6) that the parameter $\gamma \in (0,1)$ measures the level of substitutability (or similarity) between the product sold by the seller and the product sold by the platform.[16]

Because of the seller's spillover effect caused by the platform's entry as explained above, the seller's "effective" market potential is now increased from k (in setting (N)) to βk (in setting (E)), where $\beta \geq 1$. Also, to model the platform's organic demand, we model the platform's market potential as αk, where $\alpha \geq 0$. This organic demand captures the platform's "reputation effect" that is relative to the seller. As explained in Shen et al. (2020), the platform (e.g., JD.com, Amazon, etc.) has a better reputation than a typical third-party seller because of its service quality (more reliable delivery service, simpler return policy, etc.), which drives the organic demand αk. This being said, we do not restrict the relationship between α and β to make the analysis more general, and α can be either larger or smaller than β.

[16] As $\gamma \to 1$, the two products become perfect substitutes; and as $\gamma \to 0$ they become independent. Note that $u(.,.)$ is decreasing in γ, capturing the consumer's preference for product variety.

By considering the first-order conditions of (6) with respect to d_S and d_P, we get the standard linear demand functions for both parties:

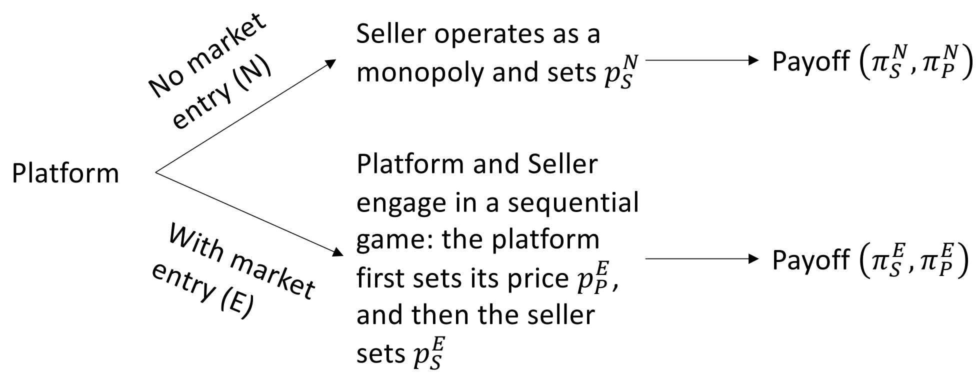
$$d_S(p_S, p_P) = \frac{\beta k - \alpha k \gamma - p_S + \gamma p_P}{1-\gamma^2}, \tag{7}$$

$$d_P(p_S, p_P) = \frac{\alpha k - \beta k \gamma - p_P + \gamma p_S}{1-\gamma^2}. \tag{8}$$

5.2. Modeling Framework: Setting (N) vs. Setting (E)

Figure 1 depicts settings (N) and (E). In setting (N), the seller operates as a monopoly by selecting his selling price p_S^N so that the seller earns π_S^N and the platform earns π_P^N (from commissions).

Figure 1 Model Framework: No Market Entry (N) vs. With Market Entry (E).



In setting (E), both parties engage in a *sequential game* as follows. The platform acts as the leader by setting her price p_P^E upon entering the market. Upon observing the platform's price p_P^E, the seller acts as the follower by selling at p_S^E. By solving this game via backward induction, we can obtain the equilibrium payoffs for both parties (π_S^E, π_P^E). As the leader, the platform will enter the market if $\pi_P^E > \pi_P^N$ and the game ends.[17]

5.3. Analysis of Setting (N): No Market Entry

When the platform does not enter the market in setting (N), the seller's monopolistic demand is $d_S = k - p_S$ as given in (5) and his net profit margin per unit is $(1-\phi)p_S - c$, where ϕ is the platform's commitment rate and $c \in (0,1)$ is the unit cost of the product. Hence, the seller's profit π_S and the platform's commission income π_P (based on the seller's revenue) are:

$$\pi_S = ((1-\phi)p_S - c)\, d_S = ((1-\phi)p_S - c)\,(k - p_S), \tag{9}$$

$$\pi_P = \phi p_S d_S = \phi p_S\,(k - p_S). \tag{10}$$

[17] Once the platform selects her equilibrium price p_P^E, the seller has no incentive to change his equilibrium price p_S^E because the seller will not be better off by deviating from this equilibrium price. In practice, both parties are likely to adjust their prices repeatedly over time because both parties have to learn about the dynamic market conditions due to changing consumer preferences, new entries of platforms and sellers, and new product introductions. The analysis of a repeated sequential game with learning and uncertain market disruptions is beyond the scope of this paper, and we shall relegate these issues to future research.

To ensure a strictly positive demand and an effective profit margin for the seller, we assume:

ASSUMPTION 1 **(Commission Rate and Unit Cost)**. $c < (1-\phi)k$.

This is a mild assumption, and the seller will not sell through the platform when the commission rate ϕ or the unit cost c is too high. By considering the first order condition of (9), we get:

PROPOSITION 1 **(Monopoly Price and Profits)**. *Without the platform's entry in setting (N), the seller's optimal price p_S^N, profit π_S^N and the platform's commission income π_P^N are:*

$$p_S^N = \frac{(1-\phi)k + c}{2(1-\phi)}, \tag{11}$$

$$\pi_S^N = (1-\phi)\left(\frac{(1-\phi)k - c}{2(1-\phi)}\right)^2, \tag{12}$$

$$\pi_P^N = \frac{\phi}{4}\left(k^2 - \left(\frac{c}{1-\phi}\right)^2\right). \tag{13}$$

Proof of Proposition 1 and all other proofs are provided in the Appendix.

Assumption 1 ensures that the seller's resulting demand $d_S^N = k - p_S^N = \frac{(1-\phi)k-c}{2(1-\phi)}$ is positive so that the profit of both parties are positive. Also, Proposition 1 reveals the aligned incentives between the platform and the seller, because the seller's profit and the platform's commission (based on the seller's revenue) are both increasing in the seller's market potential k and decreasing in c. Finally, observe that, as the commission rate ϕ increases, the seller's price p_S^N will increase, and the corresponding demand d_S^N will decrease.

5.4. Analysis of Setting (E): With Market Entry

We now analyze the sequential game as depicted in Figure 1 in §5.2 via backward induction. To begin, we solve the seller's problem for any given price p_P selected by the platform upon entry.

5.4.1. The seller's problem. For any given platform's price p_P, we can use the seller's demand function $d_S(p_S, p_P)$ given in (7) to derive the seller's profit function as:

$$\pi_s(p_S, p_P) = ((1-\phi)p_S - c)\cdot d_S(p_S, p_P) = ((1-\phi)p_S - c)\frac{\beta k - \alpha k\gamma - p_S + \gamma p_P}{(1-\gamma^2)}.$$

In preparation, let us define two terms y and z that will simplify our analysis, where:

$$y \equiv (1-\phi)\beta k - c, \text{ and } \; z \equiv \alpha k - p_P. \tag{14}$$

Observe that $y > 0$ because of Assumption 1 and the spillover effect $\beta \geq 1$. Also, z can be interpreted as the platform's monopolistic demand, where $z = \alpha k - p_P$.[18] To ease our exposition, we can replace p_P with z in our analysis. By using y and z, the seller's profit function can be simplified as:

$$\pi_S(p_S, z) = ((1-\phi)p_S - c)\frac{\beta k - \gamma z - p_S}{(1-\gamma^2)}. \tag{15}$$

[18] If the platform enters and the seller exits, then it follows from (8) that the platform's demand reduces to $z = \alpha k - p_P$.

By considering the first order condition with respect to p_S, we can determine the seller's best response price $p_S(z)$ and the corresponding seller's demand and profit in terms of y and z as follows:

LEMMA 1 **(Seller's Best Response)**. *For any given platform price p_P, the seller's best response price is $p_S(z)$, where*

$$p_S(z) = \frac{(1-\phi)\beta k - (1-\phi)\gamma(\alpha k - p_P) + c}{2(1-\phi)} = \frac{y - (1-\phi)\gamma z + 2c}{2(1-\phi)}. \tag{16}$$

Also, the corresponding seller's demand and profit can be written as:

$$d_S(z) = \frac{((1-\phi)\beta k - c) - (1-\phi)\gamma(\alpha k - p_P)}{2(1-\phi)(1-\gamma^2)} = \frac{y - (1-\phi)\gamma z}{2(1-\phi)(1-\gamma^2)}, \tag{17}$$

$$\pi_S(z) = \frac{[((1-\phi)\beta k - c) - (1-\phi)\gamma(\alpha k - p_P)]^2}{4(1-\phi)(1-\gamma^2)} = \frac{(y - (1-\phi)\gamma z)^2}{4(1-\phi)(1-\gamma^2)}. \tag{18}$$

Consistent with Proposition 1, Lemma 1 states that the seller's best response price $p_S(z)$ is increasing in c whereas the seller's profit is decreasing in c. Also, observe from the above lemma that the seller's best response price $p_S(z)$ is increasing in the platform's entry price p_P (through z), increasing in the seller's spillover effect β (through y), but it is decreasing in the platform's reputation effect α (through z). Similar observations can be made about the seller's demand and profit.

Finally, by noting that $y = (1-\phi)\beta k - c$, one can check that the seller's price $p_S(z)$ is increasing in the platform's commission rate ϕ, but the seller's demand $d_S(z)$ is decreasing in ϕ. Despite the underlying competition in setting (E), the seller would behave in the same manner as in setting (N) as stated in Proposition 1.

5.4.2. The platform's problem. Anticipating the seller's best response as stated in Lemma 1, the platform can determine its optimal entry price. In preparation, let us substitute the seller's best response price $p_S(z)$ into (8) and use the terms y and z so that the platform's demand function (in anticipation of the seller's best response) can be simplified as:

$$d_P(z) = \frac{(2-\gamma^2)z}{2(1-\gamma^2)} - \frac{\gamma y}{2(1-\phi)(1-\gamma^2)}. \tag{19}$$

Then, based on the seller's best response in Lemma 1 and the platform's demand $d_P(p_P)$ given in (19), we can use $y = ((1-\phi)\beta k - c$ and $z = \alpha k - p_P$ to simplify the platform's profit function as:[19]

$$\begin{aligned} \pi_P(z) &= \phi p_S(p_P) \cdot d_S(p_P) + (p_P - c) \cdot d_P(p_P) \\ &= \phi \left(\frac{y - (1-\phi)\gamma z + 2c}{2(1-\phi)} \right) \left(\frac{y - (1-\phi)\gamma z}{2(1-\phi)(1-\gamma^2)} \right) + ((\alpha k - c) - z) \left(\frac{(2-\gamma^2)z}{2(1-\gamma^2)} - \frac{\gamma y}{2(1-\phi)(1-\gamma^2)} \right). \end{aligned} \tag{20}$$

[19] To ease our exposition, we assume that the platform incurs the same unit cost c. This assumption is reasonable when the platform sources the same or similar product from the same supplier used by the seller.

The first term in the first line of (20) represents the platform's commission to be collected from the seller, and the second term is the platform's profit generated from its own sales upon entry. The second line is obtained from substitution.

The platform's problem is: $\max_z \pi_P(z)$. In preparation, observe from (20) that the platform's profit function is concave in z.[20] Hence, the first order condition yields the following proposition:

LEMMA 2 **(Platform's Optimal Market Entry Price)**. *By anticipating the seller's best response, the platform's optimal market entry price is* $p_P^E = \alpha k - z^*$, *and its demand* $d_P^E = d_P(z^*) = \frac{(2-\gamma^2)z^*}{2(1-\gamma^2)} - \frac{\gamma y}{2(1-\phi)(1-\gamma^2)}$, *where* $z^* = \frac{\gamma y - \frac{\phi}{1-\phi}\gamma c + (\alpha k - c)(2-\gamma^2)}{4-(2+\phi)\gamma^2}$, *and* $y = (1-\phi)\beta k - c$.

By considering z^* given in Lemma 2 and $y = (1-\phi)\beta k - c$, we can apply the chain rule to differentiate various equilibrium outcomes with respect to various parameters. Specifically, it can be shown that the platform's optimal equilibrium price $p_P^E = \alpha k - z^*$ is decreasing in the seller's spillover effect β and increasing in the platform's commission rate ϕ. This result is intuitive. Also, we find that the platform's equilibrium price p_P^E is increasing in the platform's reputation effect α when its commission rate $\phi \leq \frac{4}{\gamma^2} - \frac{2-\gamma^2}{\gamma^2 k} - 2$. This condition implies that, when the platform's commission rate ϕ is sufficiently low, the platform with a higher reputation effect α can afford to charge a higher price in equilibrium.

Similarly, through direct substitution into Lemma 1, we can retrieve the seller's optimal price $p_S^E = p_S(z^*)$. It is easy to check that the seller's optimal price p_S^E is decreasing in the platform's reputation effect α, and increasing in the seller's spillover effect β. Also, we find that the seller's optimal price p_S^E in setting (E) exhibits the same characteristics as p_S^N in setting (N) as shown in Proposition 1 in the sense that p_S^E is increasing in the platform's commission rate ϕ. Therefore, even when the seller competes with the platform in setting (E), the seller's selling price will increase when the commission rate ϕ is higher.

Armed with these equilibrium profit and price quantities (i.e., $\pi_P^E = \pi_P(z^*)$, $\pi_S^E = \pi_S(z^*)$, $p_P^E = \alpha k - z^*$, $p_S^E = p_S(z^*)$) associated with the sequential game arising from the platform's entry in setting (E), we can proceed to compare these quantities against those optimal quantities π_P^N, π_S^N, p_S^N associated with the no market entry setting (N) as stated in Proposition 1.

5.4.3. Linking thresholds of z^* and α. Because the equilibrium quantities associated with the sequential game arising from the platform's entry in setting (E) are complex, direct comparison is unwieldy and intractable at times. However, because all expressions in setting (E) are directly related to the auxiliary variable z^* as shown in Lemma 2, the platform's market entry decision and the impact of the platform's entry on the seller's profit and price will hinge upon z^*. Therefore,

[20] This can be seen by examining the second derivative of the profit function, $\frac{d^2\pi_P(z)}{dz^2} = \frac{-4+\gamma^2(2+\phi)}{2(1-\gamma^2)} < 0$.

before making comparison, we first explore a simple property of z^* that will prove useful to determine the platform's market entry condition (i.e., the condition for $\pi_P^E > \pi_P^N$) and to examine the impact of market entry on the seller's profit and price in the next section. Specifically, by noting that $z^* = \frac{\gamma y - \frac{\phi}{1-\phi}\gamma c + (\alpha k - c)(2-\gamma^2)}{(4-(2+\phi)\gamma^2)}$, we get:

Lemma 3 **(Properties of z^*)**. *Consider the optimal auxiliary variable* $z^* = \frac{\gamma y - \frac{\phi}{1-\phi}\gamma c + (\alpha k - c)(2-\gamma^2)}{(4-(2+\phi)\gamma^2)}$ *and consider any thresholds that are independent of* α *so that* $\tau_1 < \tau_2$. *Then* $z^* > \tau_1$ *if and only if* $\alpha > f(\tau_1)$ *and* $z^* < \tau_2$ *if and only if* $\alpha < f(\tau_2)$, *where* $f(\tau) \equiv \frac{(4-(2+\phi)\gamma^2)\tau - \gamma y + \frac{\phi}{1-\phi}\gamma c}{(2-\gamma^2)k} + \frac{c}{k}$ *for any* τ.

Observe from Lemma 3 that $f(\tau)$ is linearly increasing in τ. Hence, when comparing different equilibrium quantities that involve $\pi_P^E = \pi_P(z^*)$, $\pi_S^E = \pi_S(z^*)$, $p_P^E = \alpha k - z^*$, and $p_S^E = p_S(z^*)$ through z^*, these comparisons will naturally reduce to certain conditions that are based on whether z^* is above or below certain thresholds. Then, by applying Lemma 3, we can link these conditions based on z^* to conditions based on α through the linearly increasing function $f(.)$. This approach simplifies our analysis when we examine the impact of the platform's entry on the seller's optimal price and profit and the platform's market entry decision in the next section.

5.5. Impact of Platform's Entry and Platform's Entry Decisions

Our intent is to analytically examine the impact of the platform's entry on the seller's selling price and profit with the hope to provide a plausible explanation for our empirical results established in §4.3, With this goal in mind, let us first examine the conditions under which both the seller and the platform can co-exist upon the platform's entry in the following lemma:

Lemma 4 **(Range of Market Potential α for the Platform's Entry)**. *Consider two thresholds* $\underline{\alpha} = f(\frac{\gamma y}{(1-\phi)(2-\gamma^2)})$ *and* $\bar{\alpha} = f(\frac{y}{(1-\phi)\gamma})$ *that satisfy* $\underline{\alpha} < \bar{\alpha}$, *where* $f(\tau) \equiv \frac{(4-(2+\phi)\gamma^2)\tau - \gamma y + \frac{\phi}{1-\phi}\gamma c}{(2-\gamma^2)k} + \frac{c}{k}$ *for any* τ *as given in Lemma 3. Then, upon the platform's entry:*

(i) The seller's demand and profit are strictly positive (i.e., $d_S^E > 0$ *and* $\pi_S^E > 0$*) if and only if the platform's market potential* $\alpha < \bar{\alpha}$,

(ii) The platform's demand is strictly positive ($d_P^E > 0$*) if and only if* $\alpha > \underline{\alpha}$, *and*

(iii) The platform's profit upon entry is strictly positive ($\pi_P^E > 0$*) if* $\alpha > \underline{\alpha}$.

Lemma 4 identifies the range of platform's market potential $\alpha \in (\underline{\alpha}, \bar{\alpha})$ within which both the platform and the seller can co-exist profitably upon the platform's entry. Observe that $\underline{\alpha} = f(\frac{\gamma y}{(1-\phi)(2-\gamma^2)})$, $\bar{\alpha} = f(\frac{y}{(1-\phi)\gamma})$, and $y = (1-\phi)\beta k - c$. These observations imply that both bounds (i.e., $\underline{\alpha}$ and $\bar{\alpha}$)) are increasing in the spillover effect β. Therefore, as the seller's spillover effect β becomes stronger, the platform's entry condition holds when the platform's reputation effect α is sufficiently strong to ensure $\alpha \in (\underline{\alpha}, \bar{\alpha})$.

We now interpret Lemma 4. First, observe from Lemma 1 that the seller's best response price $p_S(z^*)$ and the best response demand $d_S^E = d_S(z^*)$ are strictly decreasing in the platform's reputation effect α (through z^*). Hence, when the platform market potential is too high (i.e., when $\alpha > \bar{\alpha}$), $d_S^E < 0$ and the seller will exit, which explains statement (i). Next, observe from (19) that the platform's demand $d_P^E = d_P(z^*)$ is increasing in its market potential α but $d_P^E = d_P(z^*) < 0$ when the platform's market potential is too low (i.e., when $\alpha < \underline{\alpha}$). Therefore, the platform will not enter the market when the market is not attractive. This observation explains statements (ii) and (iii).

Lemma 4 reveals that, when the platform's market potential $\alpha \in (\underline{\alpha}, \bar{\alpha})$, the platform can afford to enter the market, and the seller can adjust his selling price to compete and subsist in the market. However, the platform will enter the market only if her profit is higher (i.e., only when $\pi_P^E > \pi_P^N > 0$). We shall identify the platform's entry condition next.

5.5.1. Platform's Co-existent Entry Conditions. Lemma 4 provides the "prerequisite" condition (i.e., $\alpha > \underline{\alpha}$) for the platform's entry that ensures its profit $\pi_P^E > 0$ with $d_P^E > 0$. Also, Lemma 4 offers the condition (i.e., $\alpha < \bar{\alpha}$) under which the seller's profit is positive upon the platform's entry. Keeping the co-existence range $\alpha \in (\underline{\alpha}, \bar{\alpha})$ in mind, we aim to establish the platform's entry conditions that can ensure $\pi_P^E > \pi_P^N$ (i.e., the platform earns a higher profit upon entry) and $\pi_S^E > 0$ (i.e., the seller will stay upon the platform's entry).

Observe that the expression for the platform's profit $\pi_P^E = \pi_P(z^*)$ upon entry in setting (E) stated in (20) is highly complex, a direct analytical comparison between π_P^E in setting (E) and π_P^N in setting (N) to establish the platform's entry condition is intractable. Fortunately, through indirect comparisons, we can established a condition for the platform to enter the market without forcing the seller to exit the market in the following proposition.

Proposition 2 **(Platform Co-existent Entry Conditions)**. *Suppose the seller's spillover effect $\beta > 1$ is strong enough so that $\frac{(1-\phi)\beta k - c}{(1-\phi)k - c} > \frac{(2-\gamma^2)}{2(1-\gamma^2)} > 1$. Then there exists a threshold $t_1 \in (\underline{\alpha}, \bar{\alpha})$, where $t_1 = f(\frac{y-[((1-\phi)k-c)]}{(1-\phi)\gamma})$, such that the platform can enter the market profitably without forcing the seller to exit the market (i.e., $\pi_P^E > \pi_P^N$ and $\pi_S^E > 0$) if $\alpha \in (\underline{\alpha}, t_1)$.*

Proposition 2 highlights the role of the seller's spillover effect β and the platform's reputation effect α on the platform's co-existent entry, which enables the platform to be better off (i.e., $\pi_P^E > \pi_P^N$) and the seller to survive (i.e., $\pi_S^E > 0$) upon the platform's entry. First, Proposition 2 implies that, without the spillover effect upon the platform's entry (i.e., when $\beta = 1$), the seller's demand d_S^E and the seller's price p_S^E would be reduced upon the platform's entry due to competition and the absence of the spillover effect. Hence, upon entry, the decline in the platform's commission earnings may overshadow the profit generated from selling its own product upon entry. As such, a sufficiently strong spillover effect β that satisfies $\frac{(1-\phi)\beta k-c}{(1-\phi)k-c} > \frac{(2-\gamma^2)}{2(1-\gamma^2)} > 1$ is the first requirement to ensure an adequately high commission earning for the platform (i.e., $\phi p_S^E d_S^E$) upon its entry. Second, an additional requirement is that the platform's reputation effect has to be sufficiently high, that is, $\alpha \in (\underline{\alpha}, t_1)$. When α is sufficiently high, the platform's demand $d_P^E > 0$ upon entry (see Lemma 4), and the seller's demand d_S^E is sufficiently high to ensure that the platform's profit (based on the commissions collected from the seller and the profit generated from selling its own product) is higher upon entry.

By examining Proposition 2, we can conclude that the platform can benefit from entering the market without forcing the seller to exit when the seller's spillover effect β is strong enough and the platform's reputation effect α is moderate (i.e., when $\alpha \in (\underline{\alpha}, t_1)$. Also, by considering that $t_1 \equiv f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma})$ and $\underline{\alpha} \equiv f(\frac{\gamma y}{(1-\phi)(2-\gamma^2)})$, Proposition 2 states that the length of this range $(t_1 - \underline{\alpha})$ is equal to $f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}) - f(\frac{\gamma y}{(1-\phi)(2-\gamma^2)})$. Because $f(.)$ is a linear function, this length is linearly proportional to $[\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma} - \frac{\gamma y}{(1-\phi)(2-\gamma^2)}]$. Hence, when β is sufficiently high, Proposition 2 reveals that this length is positive. More importantly, this length is wider when the spillover effect β is higher or when the unit cost c is lower. This observation suggests that the platform's co-existent entry conditions is more likely to hold when β is higher and when the unit cost c is low. This market environment provides some insight into the conditions when it is beneficial for the platform to enter the market without squeezing the seller out.

Linking thresholds t_1 and $\underline{\alpha}$ with β. Proposition 2 reveals that the platform's co-existent entry conditions are: (a) $\frac{(1-\phi)\beta k-c}{(1-\phi)k-c} > \frac{(2-\gamma^2)}{2(1-\gamma^2)} > 1$; and (b) $\alpha \in (\underline{\alpha}(y), t_1(y))$. Here, condition (a) depends on the spillover effect β only; however, condition (b) depends on the reputation effect α directly and the spillover effect β indirectly (through $y = ((1-\phi)\beta k - c$ via two thresholds $\underline{\alpha}(y)$ and $t_1(y)$). While these two effects α and β are associated with the platform and the seller, they are assumed to be independent. However, it is possible that these two effect are correlated. For instance, if the platform has a stronger reputation effect α to create a strong awareness of similar products, it may create a stronger effect β for the seller as well. These observations motivate us to examine the platform's co-existent entry conditions as a function of the spillover effect β in the following corollary.

Corollary 1. *For any $\beta > 1$ that satisfies $\frac{(1-\phi)\beta k-c}{(1-\phi)k-c} > \frac{(2-\gamma^2)}{2(1-\gamma^2)}$, the thresholds $\underline{\alpha}$ and t_1 given in Proposition 2 possess the following properties: (a) $t_1 > \underline{\alpha}$ for any β; and (b) both $\underline{\alpha}$ and t_1 are increasing in β. Also, if the substitution factor $\gamma < x_1$ and the spillover effect $\beta > x_2$, then $\beta \in (\underline{\alpha}, t_1)$.*[21]

[21] The expressions for x_1 and x_2 are provided in the proof.

Corollary 1 has the following implications. First, if the substitution factor γ is not too high and the spillover effect is sufficiently high, then the thresholds $\underline{\alpha}$ and t_1 stated in Proposition 2 are increasing in β, so that β is bounded between $\underline{\alpha}$ and t_1. Second, in the event when the reputation effect α is correlated with the spillover effect β so that $\alpha = \beta$, Corollary 1 and Proposition 2 imply that the co-existent entry conditions hold. Hence, in the event when $\alpha = \beta$, the platform can enter the market profitably without forcing the seller to exit the market.

5.5.2. Impact of the Platform's Co-existent Entry on the Seller. After establishing the platform's co-existent entry conditions as stated in Proposition 2, we now examine the impact of such an entry on the seller's profit, price, and demand. By definition and Lemma 4, the platform's co-existent entry will ensure that the seller's profit $\pi_S^E > 0$. The specific question that remains is, specifically, under what conditions the seller would charge a higher price (i.e., $p_S^E > p_S^N$), obtain a higher demand (i.e., $d_S^E > d_S^N$), and earn a higher profit (i.e., $\pi_S^E > \pi_S^N$) upon the platform's entry in equilibrium? We examine this question in the following two propositions.

Proposition 3 **(Impact of Co-existent Entry on the Seller's Profit)**. *Suppose that the platform enters the market under the platform's co-existent entry conditions as stated in Proposition 2. Then such entry will enable the seller to increase his profit (i.e., $\pi_S^E > \pi_S^N$).*

The above proposition shows that the incumbent seller will actually benefit from the platform's entry if the platform's entry is based on the co-existent entry conditions; i.e., when the seller's spillover effect β induced by the platform's entry is strong enough and when the platform's reputation effect is moderate; i.e., when $\alpha \in (\underline{\alpha}, t_1)$. The intuition behind this result is as follows. When the platform's reputation effect α is below t_1 and the seller's spillover effect β is strong enough, the damage caused by the platform's entry due to the platform's moderate reputation effect α is low. However, the benefit (higher demand for the seller) associated with the seller's strong spillover effect β triggered by the platform's entry is high. When the benefit outweighs the damage caused by the platform's entry, the seller can earn a higher profit upon the platform's entry so that $\pi_S^E > \pi_S^N$. By combining the results stated in Proposition 2 and Proposition 3, we can conclude that the platform's co-existent entry conditions can create a "win-win" situation that would enable both the seller and the platform to benefit from the platform's entry.

Proposition 3 reveals that the platform's entry can boost the seller's profit partly because of the spillover effect β. To link this result back to our empirical analysis as shown in §4, we now explore the roles of the spillover effect β and the reputation effect α on the seller's price p_S^E and demand d_S^E. Specifically, we are interested in establishing the conditions under which the seller will increase his selling price ($p_S^E > p_S^N$), and obtain a higher demand ($d_S^E > d_S^N$) upon the platform's entry in equilibrium. We provide these conditions in the following proposition that can serve as a plausible explanation for the empirical finding that indicates $p_S^E > p_S^N$ and $d_S^E > d_S^N$ in Table 4 of §4.3.

Proposition 4 **(Impact of Co-existent Entry on the Seller's Price and Demand)**. *Suppose that the platform enters the market under the platform's co-existent entry conditions as stated in Proposition 2. Then such entry will enable the seller to increase his price (i.e., $p_S^E > p_S^N$) and obtain a higher demand (i.e., $d_S^E > d_S^N$).*

Proposition 4 can be explained as follows. The seller's optimal price in setting (N) $p_S^N = \frac{(1-\phi)k+c}{2(1-\phi)}$ is independent of α and β whereas its optimal price in setting (E) $p_S^E = \frac{y-(1-\phi)\gamma z^*+2c}{2(1-\phi)}$ is increasing in the seller's spillover effect β and decreasing in the platform's reputation effect α. As such, when α is moderate (i.e., when $\alpha \in (\underline{\alpha}, t_1)$) and when β is sufficiently high as stated in the the platform's co-existent entry conditions as stated in Proposition 2, the seller can afford to increase his selling price upon the platform's entry so that $p_S^E > p_S^N$.

In the same vein, the seller's optimal demand in setting (N) $d_S^N = \frac{(1-\phi)k-c}{2(1-\phi)}$ is independent of α and β. Also, observe that the seller's optimal equilibrium demand in setting (E) is $d_S^E = \frac{y-(1-\phi)\gamma z^*}{2(1-\phi)(1-\gamma^2)}$, which is increasing in β and decreasing in α. By combining these observations and by using the same argument as before, we can conclude that, when the platform enters the market under the conditions as stated in Proposition 2, the seller can obtain a higher equilibrium demand upon the platform's entry (i.e., $d_S^E > d_S^N$) mainly because the spillover effect β is sufficiently high and yet the reputation effect α is moderate.

In summary, by combining the results as stated in Propositions 2-4, we can conclude that the platform's entry can create a win-win situation when the platform's reputation effect α is moderate (i.e., when $\alpha \in (\underline{\alpha}, t_1)$) and when the seller's spillover effect $\beta > 1$ is sufficiently strong (i.e., when $\frac{(1-\phi)\beta k-c}{(1-\phi)k-c} > \frac{(2-\gamma^2)}{2(1-\gamma^2)} > 1$). This co-existent entry conditions provide a plausible explanation for empirical observation that the seller sets a higher equilibrium price $p_S^E > p_S^N$ and obtains a higher equilibrium demand $d_S^E > d_S^N$ as shown in Table 4 of §4.3.

6. Conclusion

Online market platforms often enter the market to compete in product spaces occupied by third-party sellers. Because of the underlying informational advantage, there is public concern about fair competition associated with the platform's market entry. This paper represents an initial attempt to examine the platform's market entry behavior and the impact of the platform's entry on the sellers.

Our exploratory analysis revealed two unexpected results: Upon the platform's entry, the seller can afford to charge a higher price and can sell more. To examine whether these two empirical results are rational, we developed a parsimonious model to show that, when the seller's spillover effect (induced by the platform's entry) is sufficiently high and when the platform's reputation effect is moderate, the platform's entry can create a win-win situation so that both the seller and the platform can earn more under the co-existent market entry conditions.

Our paper contributes to the heated debate on whether platforms' policies of entering their own market to compete with their sellers harms the sellers. In contrast to the popular conceptions (e.g., public hearings), we show that the platform's entry can benefit the sellers if the platform's entry satisfies the co-existent entry conditions.

The inevitable limitations of our study represent opportunities for future research. First, we do not observe seller IDs in the data and are therefore unable to undertake an empirical analysis of sellers' assortment decisions or product innovation efforts following JD.com's entry. Second, because the SKU IDs are seller-specific rather than product-specific, we cannot tell whether two SKUs are identical and therefore need to conduct the empirical analysis at the broader "product space" level. Third, our data cover only the transactions from a single month, so we cannot establish causality. Fourth, a critical condition for the win-win situation associated with platform entry is that the platform's entry creates a sufficiently strong spillover effect on the seller. While this is supported by our empirical results and previous research (Handarkho 2020, Kang 2017), it may fail to be met in certain markets. Finally, we do not explicitly model the process by which consumers form their choice sets. Empirically testing some of these implications would be a fruitful area for further exploration.

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Appendix

Proof of Proposition 1. Differentiate the seller's profit π_S given in (9) and consider the first order condition to obtain the optimal price p_S^N as stated in (11). Then the seller's optimal profit and the platform's corresponding commission can be obtained via direct substitution of p_S^N into (9) and (10). $\square$

Proof of Lemma 1. Differentiate the seller's profit π_S given in (15) and consider the first order condition to obtain the seller's best response as stated in (16). Then the corresponding seller's demand and profit can be obtained via direct substitution of $p_S(z)$ given in (16) into (7) and (15). $\square$

Proof of Lemma 2. First, we differentiate the platform's profit function $\pi_P(z)$ given in (20) with respect to z and then use first order condition to determine z^* as stated. Then we can retrieve the optimal value of p_P^E by using the fact that $z^* = \alpha k - p_P^E$, and retrieve the platform's demand given in (19) via direct substitution. All other comparative statics can be determined by differentiating various equilibrium outcomes and applying the chain rule $\square$

Proof of Lemma 3. Consider $z^* = \frac{\gamma y - \frac{\phi}{1-\phi}\gamma c + (\alpha k - c)(2-\gamma^2)}{(4-(2+\phi)\gamma^2)} > \tau_1$. By rearranging the terms, this inequality holds if and only if $\alpha > f(\tau_1)$. We can prove the remaining statement by using the same approach. $\square$

Proof of Lemma 4. By considering z^* given in Lemma 2 and by applying Lemma 1, we can retrieve the seller's optimal demand $d_S^E = d_S(z^*) = \frac{y-(1-\phi)\gamma z^*}{2(1-\phi)(1-\gamma^2)}$ and the seller's optimal profit $\pi_S^E = \pi_S(z^*) = \frac{(y-(1-\phi)\gamma z^*)^2}{4(1-\phi)(1-\gamma^2)}$. Hence, $d_S^E > 0$ and $\pi_S^E > 0$ if and only if $z^* < \frac{y}{(1-\phi)\gamma}$. By applying Lemma 3, we prove statement (i). To prove statement (ii), observe from (19) that the platform's demand upon entry is equal to $d_P^E = d_P(z^*) = \frac{(2-\gamma^2)z^*}{2(1-\gamma^2)} - \frac{\gamma y}{2(1-\phi)(1-\gamma^2)}$. Hence, $d_P^E > 0$ if and only if $z^* > \frac{\gamma y}{(1-\phi)(2-\gamma^2)}$. By applying Lemma 3, we prove statement (ii). Also, by noting that $\frac{y}{(1-\phi)\gamma} > \frac{\gamma y}{(1-\phi)(2-\gamma^2)}$ because $\gamma < 1$, we can conclude that $\underline{\alpha} < \bar{\alpha}$. It remains to prove statement (iii). Suppose the platform selects a particular $z = \frac{\gamma y}{(1-\phi)(2-\gamma^2)}$ so that its corresponding demand given in (19) has $d_P(z) = 0$. This way, the platform generates no profit from selling its own product. However, for this particular value of $z = \frac{\gamma y}{(1-\phi)(2-\gamma^2)}$ that is independent of α, it is easy to check that $(y - (1-\phi)\gamma z) > 0$. Combine this observation with the seller's best response quantities as stated in Lemma 1, it is immediate that the seller's best response price $p_S(z) > 0$ and the seller's best response demand $d_S(z) > 0$ for this particular value of z. Hence, the platform's commission $\phi p_S(z) d_S(z) > 0$. When the platform can earn a positive profit by selecting a non-optimal value of z, the optimal value of z^* will certainly yield a positive profit. $\square$

Proof of Proposition 2. Applying statement (i) of Lemma 4, we know that $\pi_S^E > 0$ for any $\alpha \in (\underline{\alpha}, t_1)$ as long as $t_1 < \bar{\alpha}$. We can complete the proof by finding conditions for $\pi_P^E > \pi_P^N$ below.

Observe from (20) and Lemma 2 that the platform's profit in setting (E) is $\pi_P^E = \pi_P(z^*) = \phi p_S(z^*) \cdot d_S(z^*) + (p_P(z^*) - c) \cdot d_P(z^*) = \phi p_S^E d_S^E + (p_P^E - c) d_P^E$, where $z^* = \frac{\gamma y - \frac{\phi}{1-\phi}\gamma c + (\alpha k - c)(2-\gamma^2)}{(4-(2+\phi)\gamma^2)}$. Also, from (13), the platform's profit in setting (N) is $\pi_P^N = \phi p_S^N d_S)N = \frac{\phi}{4}\left(k^2 - \left(\frac{c}{1-\phi}\right)^2\right)$. However, a direct comparison between π_P^E and π_P^N is unwieldy because of the complexity of the expression for π_P^E. Instead, by noting that the platform's profits in settings (E) and (N) are respectively $\pi_P^E = \phi p_S^E d_S^E + (p_P^E - c) d_P^E$ and $\pi_P^N = \phi p_S^N d_S^N$, we can find sufficient conditions for the platform's entry (i.e., $\pi_P^E > \pi_P^N$) that can guarantee: (1) $p_S^E > p_S^N$, (2) $d_S^E > d_S^N$, and (3) $(p_P^E - c) d_P^E = (p_P(z^*) - c) \cdot d_P(z^*) > 0$. Below, we shall establish conditions that guarantee (1) - (3) hold.

First, observe from (16) and (11) that $p_S^E > p_S^N$ if $\frac{y-(1-\phi)\gamma z^*+2c}{2(1-\phi)} > \frac{(1-\phi)k+c}{2(1-\phi)}$, where z^* is given in Lemma 2. By rearranging the term, this condition can be simplified as $z^* < \frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}$, which holds when $\alpha < t_1 \equiv f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}) < f(\frac{y}{(1-\phi)\gamma}) = \bar{\alpha}$ following Lemma 3. It remains to show that $t_1 \equiv f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}) > f(\frac{\gamma y}{(1-\phi)(2-\gamma^2)}) \equiv \underline{\alpha}$, which holds when $\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma} > \frac{\gamma y}{(1-\phi)(2-\gamma^2)}$ because the function $f(.)$ is linearly increasing. By rearranging the terms, we find that $t_1 > \underline{\alpha}$ holds when $\frac{y}{(1-\phi)k-c} \equiv \frac{(1-\phi)\beta k-c}{(1-\phi)k-c} > \frac{(2-\gamma^2)}{2(1-\gamma^2)} > 1$. Hence, we can conclude that $p_S^E > p_S^N$ when the spillover effect $\beta > 1$ is strong enough and when $\alpha \in (\underline{\alpha}, t_1)$.

Second, observe from (17), (5) and (11) that $d_S^E > d_S^N$ if $\frac{y-(1-\phi)\gamma z^*}{2(1-\phi)(1-\gamma^2)} > \frac{(1-\phi)k-c}{2(1-\phi)}$, where z^* is given in Lemma 2. By rearranging the term, this condition can be simplified as $z^* < \frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma}$, which holds when $\alpha < t_2 \equiv f(\frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma}) < f(\frac{y}{(1-\phi)\gamma}) = \bar{\alpha}$ following Lemma 3. By noting that $(\frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma} > \frac{y-((1-\phi)k-c)}{(1-\phi)\gamma})$, we can conclude that $t_2 \equiv f(\frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma}) > f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}) \equiv t_1$. Combinining these observations with our earlier arguments, we can conclude that $d_S^E > d_S^N$ when the spillover effect $\beta > 1$ is strong enough and when $\alpha \in (\underline{\alpha}, t_1)$.

Third, it remains to show that $(p_P^E - c)d_P^E = (p_P(z^*) - c) \cdot d_P(z^*) > 0$. From Lemma 4, we can conclude that $d_P^E = d_P(z^*) > 0$ for $\alpha \in \left(\underline{\alpha} \equiv f(\frac{\gamma y}{(1-\phi)(1-\gamma^2)}), t_1\right)$. It remains to show that the profit margin $(p_P(z^*) - c) = (\alpha k - c - z^*) > 0$ via contradiction. Suppose this condition does not hold. Then $(p_P(z^*) - c) = (\alpha k - c - z^*) < 0$. Now consider an alternative value of $z' = z^* - \epsilon$ so that $(p_P(z') - c) = (\alpha k - c - z') = 0$ and therefore $(p_P(z') - c)d_P(z') = 0$. By lowering the value of z^* to z', it is easy to check from (16) and (17) that the seller's price and demand will increase. Consequently, this alternative value z' will enable the platform to generate a higher profit than the profit generated by z^*, which contradicts our supposition. Hence, we can conclude that $(p_P^E - c)d_P^E > 0$. By combining all three results as stated above, we complete our proof. $\square$

Proof of Corollary 1. Because statement (a) follows immediately from Proposition 2, it suffices to focus on statement (b). In preparation, observe $y = ((1-\phi)\beta k - c)$ so that $\beta = \frac{y+c}{(1-\phi)k}$, it suffices for us to conduct our analysis in terms of y to ease our exposition. To begin, recall from Lemma 4 that $\underline{\alpha} = f(\frac{\gamma y}{(1-\phi)(2-\gamma^2)})$ and $f(\tau) \equiv \frac{(4-(2+\phi)\gamma^2)\tau - \gamma y + \frac{\phi}{1-\phi}\gamma c}{(2-\gamma^2)k} + \frac{c}{k}$ for any τ. Hence, through substitution, it is easy to check that $\underline{\alpha}$ is increasing in y if and only if $\frac{(4-(2+\phi)\gamma^2)}{(1-\phi)(2-\gamma^2)} > 1$. By rearranging the terms, this inequality holds for any ϕ and γ bounded between 0 and 1. Next, recall from Proposition 2 that $t_1 = f(\frac{y-[((1-\phi)k-c)]}{(1-\phi)\gamma})$. By direct substitution and by arranging the terms, we can use the same approach to show that t_1 is increasing in y. Then by noting that $y = (1-\phi)\beta k - c$, we can conclude that both thresholds are also increasing in β. This proves statement (b).

We now prove the last statement that $\beta \in (\underline{\alpha}, t_1)$ if $\gamma < x_1$ and $\beta > x_2$. First, through direct substitution, $t_1 > \beta$ if and only if $t_1 \equiv \frac{(4-(2+\phi)\gamma^2)(\frac{y-[((1-\phi)k-c)]}{(1-\phi)\gamma}) - \gamma y + \frac{\phi}{1-\phi}\gamma c}{(2-\gamma^2)k} + \frac{c}{k} > \frac{y+c}{(1-\phi)k} \equiv \beta$. By expanding and rearranging the terms, we can show that, after some algebra, this condition holds if and only if $(4 - 2\gamma - 3\gamma^2 + \gamma^3)y > [4 - (2+\phi)\gamma^2]((1-\phi)k - c) + \phi\gamma c(2+\gamma)(1-\gamma)$. By noting that the coefficient of y on the left hand side is positive for any $\gamma \in (0,1)$ and the right hand side is positive (due to Assumption 1 in §5.3) and by considering the supposition that $y > \frac{(2-\gamma^2)}{2(1-\gamma^2)}[(1-\phi)k - c]$, we can conclude that $t_1 > \beta$ if β is greater than a threshold x_2, where $x_2 = \frac{\max\left\{\frac{\left[4-(2+\phi)\gamma^2\right]((1-\phi)k-c)+\phi\gamma c(2+\gamma)(1-\gamma)}{4-2\gamma-3\gamma^2+\gamma^3}, \frac{2-\gamma^2}{2(1-\gamma^2)}((1-\phi)k-c)\right\}+c}{(1-\phi)k}$.

Next. through direct substitution, $\beta > \underline{\alpha}$ if and only if $\beta \equiv \frac{y+c}{(1-\phi)k} > \frac{(4-(2+\phi)\gamma^2)\frac{\gamma y}{(1-\phi)(2-\gamma^2)} - \gamma y + \frac{\phi}{1-\phi}\gamma c}{(2-\gamma^2)k} + \frac{c}{k} \equiv \underline{\alpha}$. By expanding and rearranging the terms, we can show that, after some algebra, this condition holds if and only if $[4-2(1+\phi)\gamma-4\gamma^2+(1+2\phi)\gamma^3+\gamma^4]y > -(2-\gamma^2)\phi c\,(2+\gamma)\,(1-\gamma)$. By noting that the coefficient of y on the left hand size is positive when $\gamma < x_1$ (with $x_1 < 1$) and the right hand side is always negative, we can conclude that $\beta > \underline{\alpha}$ if γ is small enough. By combining the analysis as stated above, we complete our proof. $\square$

Proof of Proposition 3. By considering z^* given in Lemma 2 and Lemma 1, we can retrieve the seller's optimal profit $\pi_S^E = \pi_S(z^*) = \frac{(y-(1-\phi)\gamma z^*)^2}{4(1-\phi)(1-\gamma^2)}$. Combine this with (12), it can be shown that $\frac{(y-(1-\phi)\gamma z^*)^2}{4(1-\phi)(1-\gamma^2)} \equiv \pi_S^E > \pi_P^N \equiv (1-\phi)\left(\frac{(1-\phi)k-c}{2(1-\phi)}\right)^2$ if and only if $z^* < \frac{y-\theta}{(1-\phi)\gamma}$, where $\theta = ((1-\phi)k-c)\sqrt{(1-\gamma^2)} > 0$. By applying Lemma 3, this condition holds if $\alpha < t_3 = f(\frac{y-\theta}{(1-\phi)\gamma})$. By noting from Proposition 2 that $\underline{\alpha} < t_1 \equiv f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma})$ and that $\theta < ((1-\phi)k-c)$, we can conclude that $t_1 < t_3$. Hence, when the platform's co-existent entry conditions as stated in Proposition 2 hold, $\pi_S^E > \pi_P^N$. This completes our proof. $\square$

Proof of Proposition 4. Observe from (16) and (11) that $p_S^E > p_S^N$ if $\frac{y-(1-\phi)\gamma z^*+2c}{2(1-\phi)} > \frac{(1-\phi)k+c}{2(1-\phi)}$, where z^* is given in Lemma 2. By rearranging the term, this condition can be simplified as $z^* < \frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}$, which holds when $\alpha < t_1 \equiv f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}) < f(\frac{y}{(1-\phi)\gamma}) = \bar{\alpha}$ when we apply Lemma 3. It remains to show that $t_1 \equiv f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}) > f(\frac{\gamma y}{(1-\phi)(2-\gamma^2)}) \equiv \underline{\alpha}$, which holds when $\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma} > \frac{\gamma y}{(1-\phi)(2-\gamma^2)}$ because the function $f(.)$ is linearly increasing. By rearranging the terms, we find that $t_1 > \underline{\alpha}$ holds when $\frac{y}{(1-\phi)k-c} \equiv \frac{(1-\phi)\beta k-c}{(1-\phi)k-c} > \frac{(2-\gamma^2)}{2(1-\gamma^2)} > 1$. Hence, when the spillover effect $\beta > 1$ is strong enough and when $\alpha \in (\underline{\alpha}, t_1)$, $p_S^E > p_S^N$ under the platform's co-existent entry conditions as stated in Proposition 2, $t_1 > \underline{\alpha}$.

Second, observe from (17), (5) and (11) that $d_S^E > d_S^N$ if $\frac{y-(1-\phi)\gamma z^*}{2(1-\phi)(1-\gamma^2)} > \frac{(1-\phi)k-c}{2(1-\phi)}$, where z^* is given in Lemma 2. By rearranging the term, this condition can be simplified as $z^* < \frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma}$, which holds when $\alpha < t_2 \equiv f(\frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma}) < f(\frac{y}{(1-\phi)\gamma}) = \bar{\alpha}$ when we apply Lemma 3. By noting that $(\frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma} > \frac{y-((1-\phi)k-c)}{(1-\phi)\gamma})$, we can conclude that $t_2 \equiv f(\frac{y-(1-\gamma^2)((1-\phi)k-c)}{(1-\phi)\gamma}) > f(\frac{y-((1-\phi)k-c)}{(1-\phi)\gamma}) \equiv t_1$. Combinining these observations with our earlier arguments, we can conclude that, when the spillover effect $\beta > 1$ is strong enough and when $\alpha \in (\underline{\alpha}, t_1)$, $d_S^E > d_S^N$. This completes our proof. $\square$

Table A-1 Correlation Matrix of Variables

Variables	If sold by JD	Total sales units	Average final price	Average lead time	Average discount rate	Att1=1	Att1=2	Att1=3	Att1=4	Att2=30	Att2=40	Att2=50	Att2=60	Att2=70	Att2=80	Att2=90	Att2=100
If sold by JD	1.000																
Total sales units	0.329***	1.000															
Avg final price	-0.005	-0.021**	1.000														
Avg lead time	-0.443***	-0.157***	-0.073***	1.000													
Avg discount rate	0.137***	0.094***	-0.094***	-0.124***	1.000												
Attribute1=1	-0.018	-0.020	-0.011	-0.023	-0.033**	1.000											
Attribute1=2	0.034**	0.012	-0.039***	0.011	0.025*	-0.091***	1.000										
Attribute1=3	0.029**	0.021	0.034**	0.021	0.020	-0.214***	-0.460***	1.000									
Attribute1=4	-0.053***	-0.024*	-0.001	-0.033	-0.028**	-0.127***	-0.273***	-0.643***	1.000								
Attribute2=30	-0.091***	-0.002	-0.011	0.002	-0.019	-0.050***	-0.325***	-0.103***	0.406***	1.000							
Attribute2=40	0.016	0.001	0.001	-0.017	-0.016	0.080***	0.136***	-0.079***	-0.060***	-0.114***	1.000						
Attribute2=50	0.008	-0.003	-0.017	0.015	0.020	0.007	0.270***	-0.132***	-0.079***	-0.166***	-0.016	1.000					
Attribute2=60	0.053***	0.002	0.171***	-0.066**	-0.036**	0.000	0.199***	-0.036***	-0.124***	-0.254***	-0.024*	-0.035**	1.000				
Attribute2=70	0.022	-0.021	-0.053***	0.036	0.026*	0.043***	0.093***	0.147***	-0.261***	-0.701***	-0.066***	-0.096***	-0.147***	1.000			
Attribute2=80	0.019	0.000	-0.019	0.034	0.014	-0.027**	0.130***	0.017	-0.114***	-0.242***	-0.023*	-0.033**	-0.051***	-0.141***	1.000		
Attribute2=90	0.095***	0.043***	-0.012	-0.068**	0.004	0.006	-0.011	0.074***	-0.076***	-0.169***	-0.016	-0.023*	-0.036***	-0.099***	-0.034**	1.000	
Attribute2=100	0.025*	0.040***	0.000	0.010	0.008	0.006	-0.032**	0.050***	-0.032**	-0.115***	-0.011	-0.016	-0.024*	-0.067***	-0.023*	-0.016	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$