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Interfaces with Other Disciplines

Dancing with rivals: How does platform's information usage benefit independent sellers?☆

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ABSTRACT

Platforms greatly facilitate transactions between buyers and sellers. At the same time, this allows platforms to gather detailed information on transactions and tailor their strategies when introducing their own products that compete with independent sellers. Concerns have been raised that such an information advantage of platforms can hurt sellers. To investigate the impact of information usage by platforms, we analyze a dynamic game-theoretic model where competing sellers trade via a platform that has access to information at various levels of granularity. We show that the usage of more detailed and individualized information by the platform can actually benefit sellers. This occurs as sellers compete less intensely, anticipating that the platform would take advantage of more individualized information to target the more successful sellers. The competition relaxing effect is particularly strong when sellers are close substitutes and face little demand uncertainty within their product category. In such cases, both the platform and sellers could benefit from more individualized information usage, but consumers may be hurt.

1. Introduction

Platforms have grown rapidly and become key players in many markets by facilitating transactions between independent sellers and consumers. For instance, in Europe, marketplaces take up 60% of cross-border e-commerce,[1] and Amazon dominates the US e-commerce market with a share above 40%.[2] As an intermediary, these platforms can gather data on trading parties at unprecedented level of scale and granularity. Some of these data are disclosed publicly whereas some others are kept privately by platforms. These data allow platforms to learn more accurately about market demand and provide valuable services to trading parties. However, recently, it has become a growing concern that platforms may use such private data to their own advantages, when they start to trade on their own platforms and compete directly with independent sellers. For instance, Amazon publishes rankings of sales aggregated at the category level, and it also has access to private data on individual sellers. It has been alleged to use private information on individual sellers to target the best selling products when introducing its private labels, although its company policy prevents the usage of such information.[3] This has triggered public debate and investigations from authorities for potential violations of antitrust laws and unsettled many independent sellers, who fear that they may be disadvantaged by the platform.[4]

To contribute to this ongoing discussion and examine the impact of a platform's use of private information, we develop a game-theoretic two-period model and consider three scenarios where the platform uses data collected in the first period at different levels of granularity, when deciding to introduce its own version of a product in the second period. In the first scenario, the platform simply introduces a product without using any first period information; in the second scenario, the platform uses information aggregated at the category level (for example, this could be the

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[1] "European e-commerce dominated by marketplaces", Retail Detail. See https://bit.ly/3o0CLsg (Accessed September 20, 2021).

[2] "Amazon dominates US ecommerce, though its market share varies by category", eMarketer. See https://bit.ly/3kwP25E (Accessed September 20, 2021).

[3] "Amazon scooped up data from its own sellers to launch competing products", Wall Street Journal. See https://on.wsj.com/33eNSls (Accessed June 17, 2020).

[4] The European Commission has found Amazon breaching EU antitrust law regarding its usage of seller information. See https://bit.ly/3Fm2wZW (Accessed September 20, 2021). The Department of Justice of the United States is under pressure to open such an investigation against Amazon for potential abuse of its market position. See https://cnb.cx/3ddx01j (Accessed June 17, 2020).

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publicly disclosed ranking of categories in the Amazon case); and in the third scenario, the platform uses information on each individual seller (for example, this could be private information in the Amazon case). Putting aside the legal matters of the current debate, we show in this article that the use of private information by the platform may actually benefit independent sellers.

We show that in the two scenarios where the platform does use information, anticipating that a better-selling category or product is more likely to attract the platform's entry, independent sellers compete less intensely in the first period. That is, the incentive to become the market leader is weakened. Such an effect is stronger when the platform has access to more detailed information, that is, when we move from the use of category information to individualized information. This benefits independent sellers by relaxing competition in the first period. Such a benefit is particularly large when competition among sellers is intense. Thus, sellers facing tough competition could benefit overall from the platform's use of more detailed information, and so does the platform. In some cases, consumers could also benefit from the platform's use of more detailed information, which better eliminates double marginalization.

Our analysis provides new insights into the discussion about a platform's collection and usage of information. We demonstrate that for the platform, it is important to consider independent sellers' strategic interactions when deciding whether and how much information on independent sellers to feed into its product development strategy. The analysis can be easily adapted to study the entry of other independent sellers, who rely on information provided by the platform. Hence, our results also shed light on a platform's information management decisions, that is, how much information to disclose to independent sellers. In addition, the results have clear regulatory implications and show the importance of considering market dynamics when investigating platforms that play the dual role of an intermediary and a trading party.

The article proceeds as follows: Section 2 reviews the relevant literature. Section 3 presents the model. The equilibrium analysis is in Section 4 and the impact of information usage on different parties is in Section 5. Section 6 studies two extensions of the model. Section 7 provides further discussions about the model and concludes with some managerial and regulatory implications of our analysis. All proofs are provided in the Online Appendix.

2. Literature review

As platforms become increasingly popular, a strand of literature has emerged to compare the traditional reselling or wholesaler mode, the platform or agency selling mode, and the hybrid mode. The focus of this strand of literature is on the optimal business mode for the retailer and the manufacturers. See, for example, Hagiu & Wright (2015), Abhishek, Jerath, & Zhang (2016), Tian, Vakharia, Tan, & Xu (2018), Yan, Zhao, & Xing (2019), Wei, Lu, & Zhao (2020), Zennyo (2020), and Wei & Dong (2022). Most of this literature focuses on a retailing platform that sells only third party products. A more recent literature has started to study the phenomenon of platforms introducing their own products to compete with third party sellers. For instance, Zhu & Liu (2018) show that Amazon is more likely to enter and compete with independent sellers, who have higher sales and better reviews and can grow with less effort. They also show that a platform's entry increases demand and reduces shipping costs but discourages sellers from growing their businesses. He, Peng, Li, & Xu (2020) demonstrate that third party sellers will migrate to other retailing channels in respond to a platform's entry. Similarly, Wen & Zhu (2019) show that Google's entry into the mobile app market shifts innovation to unaffected and new apps and may reduce wasteful development efforts. A further review of the empirical literature is provided by Zhu (2019). On the theoretical side, facing the threat of a platform's entry, a seller with private information on demand may try to hide that information from the platform by providing less services as shown by Jiang, Jerath, & Srinivasan (2011) or by downsizing the order as shown by Li, Gilbert, & Lai (2014). Both articles assume only one seller, whereas in this article, we emphasize the strategic interaction among competing sellers. In addition, we analyze different extents to which information is used by a platform. This differentiates our article from other recent contributions such as Etro (2021) and Hagiu, Teh, & Wright (2022), which focus on whether platforms should enter the product market with their own products instead of data usage by platforms. Kwark, Chen, & Raghunathan (2017) also study information usage by a platform, but their focus is again on the choice between wholesaler and platform modes but not on the comparison between different extents to which information is used.

This article is related to the literature examining the impacts of private labels on national brands in the retailing sector. For instance, Hoch (1996) gives an overview on how national brands may respond to the introduction of private labels, and Gabrielsen & Sørgard (2007) and Putsis (1997) show that national brands may price higher to soften competition with private labels. Our article differs from this literature in several ways. Firstly, the private label literature mainly studies the wholesale mode, that is, the manufacturers and the retailer negotiate on the wholesale prices and the retailer determines the retailing prices. Instead, our analysis focuses on the agency mode, that is, the platform only determines the commission fees but the sellers directly set the retailing prices for their products. Secondly, instead of focusing on the ex post impact of private labels on national brands and how national brands react, we explore the ex ante impact of potential private label introductions on competition between national brands. Thirdly, due to the vast amount of data available to platforms compared to traditional retailers, platforms are able to introduce their private labels based on different sets of information, an aspect that is not covered by the existing literature.

The mechanism we identify in this article is related to the literature on limit pricing as in Milgrom & Roberts (1982) and signal jamming as in Fudenberg & Tirole (1986). The main message from this strand of literature is that an established firm can take competitive actions to influence the inference of an entrant, so as to affect the decision of the entrant on whether to remain in or enter the market. Similar to this literature, in our model established firms (that is, independent sellers) try to manipulate the inference of an entrant (that is, the platform) to prevent entry. Yet, our article differs in several ways. Firstly, the incentives to prevent entry in this literature often intensify competition and hurt the entrant, whereas the incentives to do so in our article soften competition and could benefit both established firms and the entrant. Secondly, the existing literature focuses on horizontal competitors, firms in this article (sellers and the platform) are in a relationship with both vertical and horizontal elements, as independent sellers rely on the platform to make sales and at the same time they face potential competition from the platform.

3. The model

We consider a model of agency selling, where sellers trade with buyers via a monopolistic platform. There are different product categories and sellers within a category sell differentiated products. For the main model, we consider two categories, A and B, and two sellers in each category, namely, $A1$ and $A2$ in category A, and $B1$ and $B2$ in category B.[5] For clarity, we assume that all sellers and

[5] Our main insights would naturally extend to a setting with any finite number of sellers in a category, see Section 6 for a more detailed analysis. Our main in-

the platform (in the case of entry) produce at zero costs. However, to sell via the platform, each seller needs to pay a commission to the platform. In our main analysis, we focus on *ad valorem* or proportional commission fee, the rate of which is denoted by r. That is, the platform collects a percentage r of the total revenue from each seller.[6] For our analysis, we assume $r \leq (6-3\sqrt{2})/2 \approx 88\%$ to ensure that all sellers make positive profits across different scenarios. Proportional fees are widely observed in practice and can be justified on different grounds.[7] For example, the commission rate typically ranges from 8 to 20% on Amazon and is about 30% on Apple's App Store.[8]

For each category $i = A, B$, we denote the potential market size by ϵ_i, which is a random variable distributed on $[0, \bar{e}]$ according to $F(\epsilon_i)$, with the density function denoted by $f(\epsilon_i)$.[9] This captures demand uncertainty at the category level. Let p_{i1} and p_{i2} denote the prices of the two sellers in category i, and q_{i1} and q_{i2} the resulting demands for the two sellers. Furthermore, let β denote the degree of product differentiation, and w_{i1} and w_{i2} the product strengths for product $i1$ and $i2$, respectively. We follow Shubik & Levitan (1980) by assuming that the demands satisfy:[10]

$$q_{i1} = \epsilon_i w_{i1}(1 - p_{i1} + \beta w_{i2}(p_{i2} - p_{i1})),$$
$$q_{i2} = \epsilon_i w_{i2}(1 - p_{i2} + \beta w_{i1}(p_{i1} - p_{i2})). \tag{1}$$

That is, sellers within a category differ in two ways. Firstly, as standard in the literature, β measures the degree of product differentiation between sellers. They are independent if $\beta = 0$ and homogeneous if $\beta \to \infty$. In our main analysis with proportional fee and zero production cost, following similar steps as McGuire & Staelin (2008), we can show that β can take any non-negative value while ensuring that the equilibrium prices and quantities are interior and the demand functions are well-behaved.[11] Secondly, sellers differ in the strengths of their products, w_{ij} ($i = A, B$ and $j = 1, 2$), which can be interpreted as the market share of each seller when all sellers in the same category charge equal prices with the assumption that $w_{i1} + w_{i2} = 1$. To capture demand uncertainty within each category, we assume that $(w_{i1}, w_{i2}) = (w, 1-w)$ with probability 50%, and $(w_{i1}, w_{i2}) = (1-w, w)$ with probability 50%, with $w \in (1/2, 1]$. That is, each seller can be either the strong or the weak seller in its category.[12]

We consider the following two-period game:

- *First Period.* At the beginning of the first period, each seller chooses a price before the realization of demand uncertainties at both the category level and the individual level within a category. Then, the demand uncertainties realize and each seller obtains the corresponding profits.
- *Second Period.* After observing sales in the first period, depending on the information available, the platform decides the product to introduce its own version. Then, sellers and the platform compete and obtain the corresponding profits.

Both the sellers and the platform weigh the second period profit by δ relative to the first period profit. We can interpret the first period as the learning stage when the platform learns about product popularity, and the second period as the competition stage when the platform enters to compete with independent sellers. Then, δ measures the length of the competition stage relative to the length of the learning stage. We do not make any *a priori* assumption on the magnitude of δ, which depends on the lifecycle of a product and the speed of learning. For example, the average lifespan is about one to two years for electronics, but only a few months for fashion products on Amazon.[13] It also depends on a seller's objective, and $\delta = 0$ corresponds to the case where a seller focuses only on short-run profits. For most sellers, especially those who have established the platform as their main retailing channel, we expect δ to be positive. However, to ensure that an interior equilibrium with positive sales in the first period exists, we need δ to be not too large.[14] The constraint is more stringent under targeted entry (when the platform uses individualized information) and when competition between sellers is weak (w is high and β is low). However, when competition is intense, the second period can be significantly longer than the first period.

We focus on price competition, as price is the most important factor that influences online shoppers,[15] and sellers compete in prices to win market shares; see, for example, Cabral (2018). As sellers are symmetrically uninformed at the beginning, we focus on the symmetric subgame Nash equilibrium where all sellers charge the same price in the first period and investigate the impact of the platform's entry and information usage on the equilibrium price and payoffs of different parties.

3.1. Information usage in the second period

We start with the analysis in the second period and introduce some more notations. To reflect potential limited resources that the platform can employ to manage its supply chain, we assume the platform chooses one product to enter with its own version. As a benchmark, we consider the case where the platform does not use any first period information and enters with a randomly selected product. We call this "random entry". Alternatively, the platform can base its product selection on first period demands or the volume of sales. We distinguish between two extents to which information is used. Firstly, the platform can use information aggregated at the category level and enter with a random product in the higher first period sales category. We call this "category entry". Secondly, the platform can use detailed information on individual sellers in the first period and enter with the same product as the seller with the highest first period sales. We call this "targeted entry". As mentioned in the Introduction, information on individual sellers is often private and the use of it may potentially violate antitrust laws. Putting aside the legality of such information usage, our analysis focuses on the potential impact this has on the market outcome.

sights can also be derived in a model with one category accounting for entry cost, although this requires a different analysis and is less straightforward; see Online Appendix.

6 In the Online Appendix, we discuss how our main insights carry though to the case of a per unit fee.

7 See, for example, Shy & Wang (2011).

8 "A guide to platform fees", The Verge. See https://bit.ly/3v8Zaqg (Accessed July 24, 2022).

9 We assume that $f'(\epsilon) \geq 0$ to guarantee that the profit functions are concave.

10 The demands can be derived from the following utility function of an individual consumer for products in category i:

$$U = \tilde{q}_{i1} + \tilde{q}_{i2} - \frac{1}{2(1+\beta)}\left[\frac{(\tilde{q}_{i1})^2}{w_{i1}} + \frac{(\tilde{q}_{i2})^2}{w_{i2}} + \beta(\tilde{q}_{i1} + \tilde{q}_{i2})^2\right],$$

where $\tilde{q}_{i1}$ and $\tilde{q}_{i2}$ are the levels of consumption for product $i1$ and $i2$. The total demands for products in category i are obtained by multiplying the individual consumer's demand by the market size ϵ_i.

11 Specifically, we need the set of (p_{i1}, p_{i2}) defined by $p_{i1} \geq 0$, $p_{i2} \geq 0$, $p_{i1} \leq \frac{1+\beta w_{i2} p_{i2}}{1+\beta w_{i2}}$, and $p_{i2} \leq \frac{1+\beta w_{i1} p_{i1}}{1+\beta w_{i1}}$ to be non-empty, which is true for any β. In addition, the total demand $q_{i1} + q_{i2}$ is decreasing in both prices. Even with positive production cost, as in the case of a per unit commission fee, β can still take any non-negative value as long as the cost is below 1/2.

12 We assume there is strict uncertainty at the seller level, that is, $w > 1/2$. This is to ensure the existence of an equilibrium in the case of targeted entry.

13 "How to gauge Amazon product lifecycle". See https://bit.ly/3eJFymY (Accessed September 12, 2022).

14 See the proofs of Lemma 2 and Lemma 3 for details.

15 "When shopping online, what are the most important factors that influence you to shop at a particular retailer?", statista. See https://bit.ly/3zXYeVd (Accessed September 20, 2021).

Table 1
Summary of notations.

Notation	Description
ϵ_i	Market size of category $i, i = A, B$
$F(\epsilon_i)$	Distribution function of ϵ_i
$f(\epsilon_i)$	Density function of ϵ_i
$\bar{e}$	Upper bound of ϵ_i
β	Degree of product differentiation within a category
w_{ij}	Strength of seller $j, j = 1, 2$ in category $i, i = A, B$, taking value w or $1 - w$
q_{ij}	Demand for seller $j, j = 1, 2$ in category $i, i = A, B$
p_{ij}	First period price of seller $j, j = 1, 2$ in category $i, i = A, B$
r	Proportional commission rate
δ	Weight of the second period profit
$\pi_{ij}(w_{ij}, r; p_{ij}, p_{ij'})$	Per consumer profit of seller ij
$\pi^N(w, r)$	Second period per consumer profit of the strong seller without platform entry
$\pi^N(1 - w, r)$	Second period per consumer profit of the weak seller without platform entry
$\pi_S(w, r)$	Second period per consumer profit of the strong seller when the platform replaces the weak seller
$\pi_S(1 - w, r)$	Second period per consumer profit of the weak seller when the platform replaces the strong seller
$\pi_I(w, r)$	Second period per consumer profit of the platform when it replaces the strong seller
$\pi_I(1 - w, r)$	Second period per consumer profit of the platform when it replaces the weak seller

We assume that once the platform enters, it drives out the seller which sells the same product, and the remaining sellers within each category (original sellers or the platform) compete under full information by choosing their prices. This is mainly for tractability of the dynamic analysis, and we will discuss in Section 6 how our main insights carry through to cases where the entry of the platform does not entirely crowd out the original sellers. Hence, in the second period, we have two situations for category $i = A, B$, either the platform enters or not. Since the market size ϵ_i does not affect the pricing decisions, we focus on the profit per consumer for the remainder of this section.

Firstly, we consider the case when there is no platform entry in category i. So the two original sellers remain to compete. Each seller j chooses a price to maximize its profit per consumer, π_{ij}, given by:

$$\begin{aligned}\pi_{ij}(w_{ij}, r; p_{ij}, p_{ij'})\\ = (1 - r)w_{ij}p_{ij}(1 - p_{ij} + \beta(1 - w_{ij})(p_{ij'} - p_{ij})), \text{ for } j' \neq j. \quad (2)\end{aligned}$$

We denote the resulting competitive profit per consumer of the strong seller by $\pi^N(w, r)$ and the competitive profit per consumer of the weak seller by $\pi^N(1 - w, r)$, with a total second period profit of $\epsilon_i\pi^N(w, r)$ and $\epsilon_i\pi^N(1 - w, r)$, respectively.

Secondly, the platform enters and competes with the remaining seller. When the platform replaces the strong seller, given the remaining weak seller's price p_S, it chooses its price p_I to maximize its per consumer profit, π_I, given by:

$$\begin{aligned}\pi_I = wp_I(1 - p_I + \beta(1 - w)(p_S - p_I))\\ + r(1 - w)p_S(1 - p_S + \beta w(p_I - p_S)),\end{aligned}$$

and the remaining seller chooses p_S to maximize its per consumer profit, π_S, given by:

$$\pi_S = (1 - r)(1 - w)p_S(1 - p_S + \beta w(p_I - p_S)).$$

We denote the resulting competitive profit per consumer for the platform by $\pi_I(w, r)$ and the per consumer profit for the remaining weak seller by $\pi_S(1 - w, r)$. Similarly, when the platform replaces the weak seller, we denote the resulting competitive profit per consumer for the platform by $\pi_I(1 - w, r)$ and the per consumer profit for the remaining strong seller by $\pi_S(w, r)$. The main parameters of the model and the analysis are summarized in Table 1.

Before moving on to the analysis of first period prices, we briefly discuss the assumption on the usage of information. We focus on the information about the volume of sales. This ensures tractability of the model and allows us to deliver our main insights analytically. We show in Online Appendix that our main insights extend to the setup when the platform bases its entry on the value of sales (that is, revenue) at the category or individual levels. We can show that when competition between sellers is intense, sellers could still benefit from more individualized information usage.[16] However, this alternative model is less tractable as the prices are determined by higher-order polynomials, which makes profit comparison difficult.

In addition, for the platform, the volume of sales is a sufficient indicator for popularity and profitability on the equilibrium path. In practice, the volume of sales serves as a good starting point to identify potential popular products. For instance, Kalra & Stecklow (2021) show how Amazon (India) selected a reference product to replicate, starting from category sales, to individual sales, and then to detailed product information. Thus, the model provides a simplified yet tractable version to the more general case where the category or individual seller that obtains higher sales is more likely, if not certainly, to attract a platform's attention, which prompts subsequent detailed information analysis and entry. Moreover, Amazon publishes rankings of categories based on the volume of sales. Regulations have been proposed to break up the dual role of platforms, which means the product department of the platform would have the same information as any other third party seller.[17] Our results then show the potential impact of entrants accessing more fine-tuned public information on market outcome.

4. Strategic pricing under platform entry

4.1. No information usage: random entry or no entry

As a benchmark, we consider the case where the platform does not use any sales information from the first period. For instance, the platform could commit not to enter, or the platform could commit not to use any information and introduce its own version of a randomly selected product. In either case, the prices and sales in the first period have no effect on payoffs in the second period. Hence, the equilibrium price in the first period would be the same in both cases, denoted by p^N.

In search for such a symmetric equilibrium where all sellers charge p^N in the first period, let us assume all other sellers are charging this equilibrium price, whereas seller $A1$ contemplates to charge a slightly different price $\tilde{p}$. Under random entry, its ex-

[16] The only main difference in this case is that the price becomes lower under category entry than random entry, but the price is still higher under targeted entry compared to category entry or random entry.

[17] "The risks keep growing for Amazon third-party sellers", Forbes. See https://bit.ly/3yN52GJ (Accessed July 24, 2022).

pected profit is:

$$\Pi(\tilde{p}, p^N) = \int_0^{\bar{e}} \epsilon_A \Big(\frac{1}{2} \big(\pi_{A1}(w, r; \tilde{p}, p^N) + \delta(\frac{1}{2}\pi^N(w, r) + \frac{1}{2}\frac{\pi_S(w, r)}{2}) \big) + \frac{1}{2} \big(\pi_{A1}(1 - w, r; \tilde{p}, p^N) + \delta(\frac{1}{2}\pi^N(1 - w, r) + \frac{1}{2}\frac{\pi_S(1 - w, r)}{2}) \big) \Big) dF(\epsilon_A).$$

With probability 1/2, $A1$ is the strong seller. In the first period, it obtains a per consumer profit of $\pi_{A1}(w, r; \tilde{p}, p^N)$ as defined by Eq. (2). In the second period, with probability 1/2, the platform does not enter category A, so it obtains a profit of $\pi^N(w, r)$; with probability 1/2, the platform enters category A, but $A1$ still obtains a profit of $\pi_S(w, r)$ with probability 1/2 when the platform replaces $A2$. Alternatively, with probability 1/2, $A1$ is the weak seller and its expected profit is obtained by simply replacing w with $1 - w$.

Under no entry, the expected profit of $A1$ is:

$$\Pi(\tilde{p}, p^N) = \int_0^{\bar{e}} \epsilon_A \Big(\frac{1}{2} \big(\pi_{A1}(w, r; \tilde{p}, p^N) + \delta\pi^N(w, r) \big) + \frac{1}{2} \big(\pi_{A1}(1 - w, r; \tilde{p}, p^N) + \delta\pi^N(1 - w, r) \big) \Big) dF(\epsilon_A),$$

where it obtains $\pi^N(w, r)$ when it is the strong seller and $\pi^N(1 - w, r)$ when it is the weak seller in the second period.

To ease the exposition, we drop the subscript $A1$ from $\pi_{A1}(w, r; \tilde{p}; p^N)$ and $\pi_{A1}(1 - w, r; \tilde{p}, p^N)$ in the following analysis, and let π_p denote the corresponding first order partial derivative with respect to $\tilde{p}$. The optimal $\tilde{p}$ under both random entry and no entry then satisfies:

$$0 = \frac{\partial \Pi(\tilde{p}, p^N)}{\partial \tilde{p}} = \int_0^{\bar{e}} \epsilon_A \frac{\pi_p(w, r; \tilde{p}, p^N) + \pi_p(1 - w, r; \tilde{p}, p^N)}{2} dF(\epsilon_A).$$

We can show that:

Lemma 1. *In the case of no information usage (random entry or no entry), a symmetric equilibrium* (p^N, p^N) *exists and satisfies:*

$$0 = \int_0^{\bar{e}} \epsilon_A \frac{\pi_p(w, r; p^N, p^N) + \pi_p(1 - w, r; p^N, p^N)}{2} dF(\epsilon_A). \tag{3}$$

4.2. Usage of aggregate information: category entry

Now we consider the use of category sales information. Let $q^1_{ij}, i = A, B, j = 1, 2$ be the first period sales of each seller, and $q^1_A = q^1_{A1} + q^1_{A2}$ and $q^1_B = q^1_{B1} + q^1_{B2}$ be the total category sales. The platform enters with a random product in category i if $q^1_i > q^1_{i'}, i' \neq i$.

In the first period, each seller chooses a price to maximize its total expected profit across the two periods. Similar as above, suppose all other sellers charge the equilibrium price p^C and we consider seller $A1$ contemplating to charge a different price $\tilde{p}$. Let $Prob_s(q^1_A < q^1_B)$ denote the probability of the platform not entering category A when $A1$ is the strong seller and $Prob_w(q^1_A < q^1_B)$ the probability of the platform not entering category A when $A1$ is the weak seller. Seller $A1$'s expected profit is:

$$\Pi(\tilde{p}, p^C) = \int_0^{\bar{e}} \epsilon_A \Big(\frac{1}{2} [\pi(w, r; \tilde{p}, p^C) + \delta Prob_s(q^1_A < q^1_B)\pi^N(w, r) + \delta(1 - Prob_s(q^1_A < q^1_B))\frac{1}{2}\pi_S(w, r)] + \frac{1}{2}[\pi(1-w, r; \tilde{p}, p^C) + \delta Prob_w(q^1_A < q^1_B)\pi^N(1-w, r) + \delta(1 - Prob_w(q^1_A < q^1_B))\frac{1}{2}\pi_S(1 - w, r)] \Big) dF(\epsilon_A),$$

We can show that:

Lemma 2. *In the case of category entry, a symmetric equilibrium exists and satisfies:*

$$0 = \int_0^{\bar{e}} \epsilon_A \Big(\frac{\pi_p(w, r; p^C, p^C) + \pi_p(1 - w, r; p^C, p^C)}{2} + \frac{\delta}{2} \frac{\epsilon_A f(\epsilon_A)}{1 - p^C} M^C(w, r) \Big) dF(\epsilon_A), \tag{4}$$

where $M^C(w, r) = w(\pi^N(w, r) - \frac{\pi_S(w,r)}{2}) + (1 - w)(\pi^N(1 - w, r) - \frac{\pi_S(1-w,r)}{2})$.

4.3. Usage of individualized information: targeted entry

Finally, we consider the platform entering with the same product as the seller with the highest first period sales. Similar as above, we focus on the symmetric price equilibrium in the first period where all sellers charge a price of p^T. If all other sellers charge this equilibrium price and $A1$ contemplates to charge a different price $\tilde{p}$, its expected profit is given by:

$$\Pi(\tilde{p}, p^T) = \int_0^{\bar{e}} \epsilon_A \Big(\frac{1}{2}[\pi(w, r; \tilde{p}, p^T) + \delta(1 - Prob(q^1_{A1} = \max\{q^1_{A1}, q^1_{A2}, q^1_{B1}, q^1_{B2}\})\pi^N(w, r)] + \frac{1}{2}[\pi(1 - w, r; \tilde{p}, p^T) + \delta(1 - Prob(q^1_{A2} = \max\{q^1_{A1}, q^1_{A2}, q^1_{B1}, q^1_{B2}\})\pi^N(1 - w, r) + \delta Prob(q^1_{A2} = \max\{q^1_{A1}, q^1_{A2}, q^1_{B1}, q^1_{B2}\})\pi_S(1 - w, r)] \Big) dF(\epsilon_A).$$

When $A1$ is the strong seller, it obtains a positive profit in the second period when it is not the best seller in the first period, which occurs with probability $1 - Prob(q^1_{A1} = \max\{q^1_{A1}, q^1_{A2}, q^1_{B1}, q^1_{B2}\})$. When $A1$ is the weak seller instead, it obtains a profit of $\pi^N(1 - w, r)$ when the strong seller $A2$ is not the best seller in the first period, which occurs with probability $1 - Prob(q^1_{A2} = \max\{q^1_{A1}, q^1_{A2}, q^1_{B1}, q^1_{B2}\})$, and it obtains a profit of $\pi_S(1 - w, r)$ otherwise. We only need to consider the strong seller in each category because the product strengths can only take two discrete values w and $1 - w$, so a small deviation in price does not change the ranking of sales within a category, where the strong seller obtains the higher sales. Thus, suppose $B1$ is the strong seller in category B, when $A1$ is the strong seller in category A, it is also the best seller if $q^1_{A1} > q^1_{B1}$, that is $Prob(q^1_{A1} = \max\{q^1_{A1}, q^1_{A2}, q^1_{B1}, q^1_{B2}\}) = Prob(q^1_{A1} > q^1_{B1})$; Similarly, if $A1$ is the weak seller in category A, it cannot be the best seller and $A2$ is the best seller if $q^1_{A2} > q^1_{B1}$, that is, $Prob(q^1_{A2} = \max\{q^1_{A1}, q^1_{A2}, q^1_{B1}, q^1_{B2}\}) = Prob(q^1_{A2} > q^1_{B1})$. We can show that:

Lemma 3. *In the case of targeted entry, a symmetric equilibrium exists and satisfies:*

$$0 = \int_0^{\bar{e}} \epsilon_A \Big(\frac{\pi_p(w, r; p^T, p^T) + \pi_p(1 - w, r; p^T, p^T)}{2} + \frac{\delta}{2} \frac{\epsilon_A f(\epsilon_A)}{1 - p^T} M^T(w, r) \Big) dF(\epsilon_A), \tag{5}$$

where $M^T(w, r) = (1 + \beta(1 - w))\pi^N(w, r) - \beta(1 - w)(\pi^N(1 - w, r) - \pi_S(1 - w, r))$.

4.4. Impact of information usage

Now we are ready to show that:

Proposition 1. *The equilibrium first period price is higher when the platform uses more individualized information, that is,* $p^T > p^C > p^N$.

To understand Proposition 1, note that if $\delta = 0$, we have $p^T = p^C = p^N$ as the first period prices have no influence on the second period profits. As long as $\delta > 0$, sellers have incentives to manipulate their first period sales so as to influence the platform's entry decision. In the case of category entry, this incentive is represented by $M^C(w, r)$. Specifically, a seller ij obtains a profit of $\pi^N(w_{ij}, r)$ if there is no platform entry, which is higher than $\pi_S(w_{ij}, r)/2$ if there is platform entry (note that the platform only enters with the same product as seller ij with probability 50%). In addition, the platform's entry decision depends on the total sales of category i, for which seller ij contributes a proportion of w when it is the strong seller and a proportion of $1 - w$ when it is the weak seller. Hence, there is an incentive to lower the chance of platform entry in category i by increasing the price.

In the case of targeted entry, by comparing $M^C(w, r)$ and $M^T(w, r)$ in Lemma 2 and Lemma 3, the incentives of seller ij change in several ways. Firstly, if it turns out to be the strong seller, its own sales fully determine the probability of the platform's entry in category i, hence, the impact of its own price on whether entry occurs is larger than that under category entry and is proportional to $1 + \beta(1 - w)$ instead of w. We call this the "deaveraging effect". Secondly, if it turns out to be the strong seller, it loses the whole competitive profit $\pi^N(w, r)$ and earns zero profit in the second period in the case of targeted entry instead of earning $\pi_S(w, r)/2$ in the case of category entry. We call this the "replacement effect" for the strong seller. These two effects together mean that the seller has stronger incentives to raise price. Thirdly, if it turns out to be the weak seller, it would not be replaced when the platform enters. Hence, it earns a profit of $\pi_S(1 - w, r)$ instead of $\pi_S(1 - w, r)/2$. We call this the "replacement effect" for the weak seller. Moreover, under proportional fee, the weaker seller actually benefits from the strong seller being replaced, as the platform partially internalizes the profit of the weak seller and we have $\pi^N(1 - w, r) - \pi_S(1 - w, r) < 0$. This reduces its incentives to prevent the platform's entry. Finally, if it turns out to be the weak seller, decreasing its price actually reduces the probability of entry in category i as it decreases the sales of the strong seller, which determine the platform's entry strategy. Specifically, the impact of its price on entry becomes $-\beta(1 - w)$ instead of $1 - w$. We call this the "entry easing effect". The latter two effects also imply incentives to raise price. Altogether, sellers charge higher prices under targeted entry as shown by Proposition 1.

5. How does information usage affect different groups?

The key message from Section 4 is that competition between sellers in the first period is weakened when the platform uses more detailed sales information in determining its entry strategy. We now turn to the impacts this has on different parties.

5.1. Sellers

For sellers, targeted entry lowers the expected profit in the second period as the platform is more likely to replace the strong seller; however, targeted entry relaxes competition in the first period as sellers charge higher prices to keep the platform from entering. In balance, if the latter effect is strong enough, sellers can benefit overall. Indeed, we can show that:

Proposition 2. *There exists a $\hat{w} \in (1/2, 1]$ such that for any $w < \hat{w}$, the profits of sellers are higher under targeted entry than category entry for sufficiently large β. If $w = 1$ or $\beta = 0$, the profits of sellers are lower under targeted entry than category entry.*

Sellers benefit overall from targeted entry when competition between sellers is intense, which occurs when either β is large (so products of sellers are close substitutes) or w is small (so brand preference or demand uncertainty within a category is weak). On the other hand, when β is small or w is large, competition between sellers is weak: the products are nearly independent in the former case and the price of one product has little effect on the other's sales in the latter case. This means that the equilibrium price under random entry would be very close to the static profit maximizing price (exactly equal if $\beta = 0$ or $w = 1$), which in turn means that the price tends to be too high under category entry compared to the static profit maximizing level, and targeted entry further raises the price and reduces the profits of sellers in the first period.

The same intuition applies when comparing the profits of sellers under targeted entry and random entry, and we can show that the same result holds if ϵ_i is distributed uniformly:[18]

Proposition 3. *If $F(\epsilon_i) = \epsilon_i/\bar{e}$, there exists a $\bar{w} \in (1/2, 1]$ such that for any $w < \bar{w}$, the profits of sellers are higher under targeted entry than random entry for sufficiently large β. If $w = 1$ or $\beta = 0$, the profits of sellers are lower under targeted entry than random entry.*

Similarly, we can show that the profits of sellers are always lower under category entry than random entry when $w = 1$ or $\beta = 0$. However, when $w \to 1/2$, the profits are still lower under category entry even if $\beta \to \infty$. Our numerical results show that the profits of sellers are always lower under category entry than random entry when ϵ_i follows the uniform distribution, that is, under category entry the benefit of softened competition in the first period is not strong enough to compensate the loss in the second period caused by the platform's entry.

Finally, we consider no entry. The profits of sellers under no entry are higher than random entry, which means they are also higher than under category entry. However, sellers' profits can be higher under targeted entry than no entry, when competition is intense enough.

Proposition 4. *If $F(\epsilon_i) = \epsilon_i/\bar{e}$, there exists a $\tilde{w} \in (1/2, 1]$ such that for any $w < \tilde{w}$, the profits of sellers are higher under targeted entry than no entry for sufficiently large β.*

Under proportional fee, sellers could actually benefit from more information usage by the platform, so they would prefer the platform to enter rather than not entering, especially when competition among sellers is sufficiently intense. This is illustrated in Fig. 1 with different commission rates.

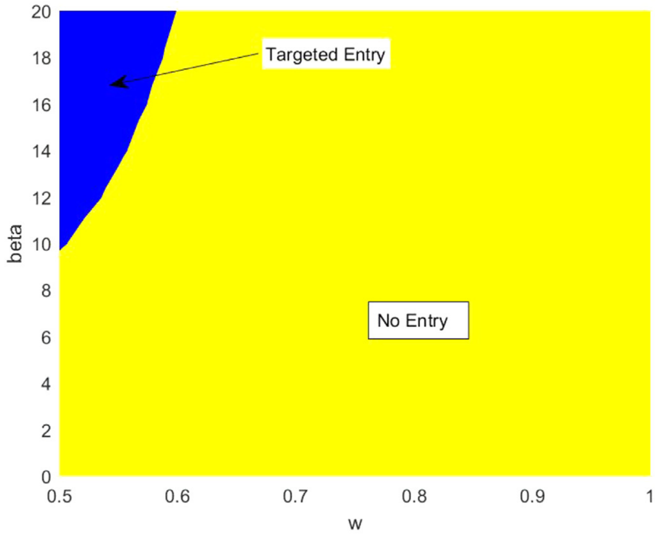
5.2. Platform

For the platform, clearly, no entry is dominated by random entry, due to the gains from sales in the second period. Hence, in the following of this section, we focus on the comparison between random entry, category entry, and targeted entry. If the commission fees are zero, the platform does not earn anything from sellers in the first period but it clearly benefits from more information usage in the second period, as it can guarantee itself to sell the more popular product under targeted entry. Therefore, it benefits overall. The same intuition holds when r is sufficiently small:

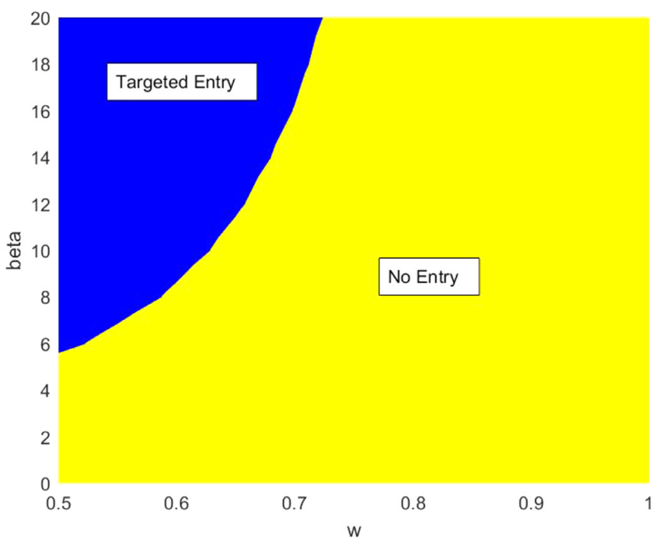
Proposition 5. *For given w and β, there exists $\bar{r}(w, \beta)$ such that the platform's profit is higher under targeted entry than under category entry, and both are higher than under random entry, if $r < \bar{r}(w, \beta)$.*

Given the intensity of seller competition, the platform generally prefers entry with more detailed information when the fees are sufficiently low, as the second period gains dominate any potential losses in the first period. Such losses occur under proportional

[18] A comparison of profits for a general distribution function $F(\epsilon_i)$ is complex due to high non-linearity in profit functions and depends on the exact shape of the distribution function.



(a) Low Commission Fee ($r = 0.4$)



(b) High Commission Fee ($r = 0.8$)

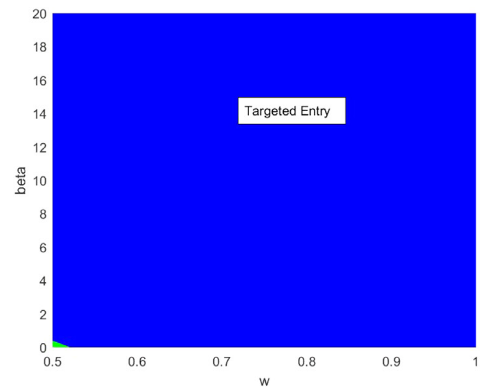
Fig. 1. Seller's Preferred Entry Mode under Proportional Fee ($\delta = 0.7$).

fee when competition is weak as the equilibrium prices are higher than the static profit maximizing prices. Therefore, when commission fees are sufficiently low, both the platform and sellers prefer targeted entry when competition between sellers is intense.

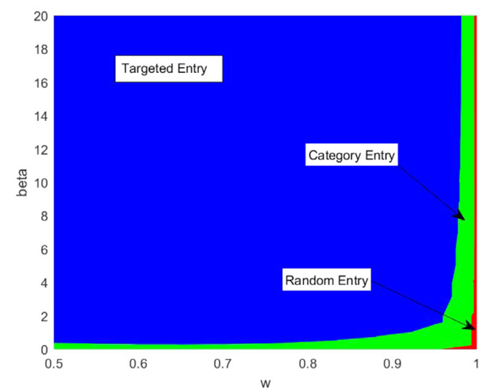
As long as the intensity of seller competition is sufficiently strong, the platform prefers targeted entry even for higher proportional fees, as the platform and sellers have aligned interests. If sellers benefit overall, they must earn higher profits in the first period given that they are hurt in the second period. This means the platform also earns more in the first period, hence, it benefits overall. That is:[19]

Proposition 6. *The profit of the platform is higher under targeted entry whenever the profits of sellers are higher under targeted entry compared to category entry or random entry.*

However, their interests are less aligned when competition between sellers is weak. The sellers are hurt by targeted entry in such cases, but the platform still prefers targeted entry in order to reap the benefit in the second period.



(a) Low Commission Fee ($r = 0.4$)



(b) High Commission Fee ($r = 0.8$)

Fig. 2. The Platform's Preferred Entry Mode under Proportional Fee ($\delta = 0.7$).

It may be tempting to think that the platform prefers targeted entry when demand uncertainty within a category is high, that is, when w is high, as the benefit of entering with the strong product is larger. However, the platform's relative preference for targeted entry can be non-monotone in w, and its profit can be lower under targeted entry than category entry for sufficiently large w. For instance, at $w = 1$ and with uniformly distributed ϵ_i, we can show that under proportional fee, the profit of the platform is lower under targeted entry than under category entry if:

$$\frac{1}{2}\Big(\frac{2\sqrt{3}}{\sqrt{3-2\delta}+\sqrt{3-4\delta}}-1\Big) > \frac{1-r}{r},$$

and lower than under random entry if:

$$\frac{4}{5}\Big(\frac{2\sqrt{3}}{\sqrt{3}+\sqrt{3-4\delta}}-1\Big) > \frac{1-r}{r},$$

both conditions are satisfied when r and δ are large enough.

The intuition is as follows: Under proportional fee, at $w = 1$, the random entry equilibrium price is the static profit maximizing price, and thus the equilibrium prices under both category entry and targeted entry are above the static profit maximizing price, which means lower profits for sellers in the first period. When r is large, the platform puts a higher weight on the revenues of sellers, which are more negatively affected by higher prices under targeted entry. Moreover, such an upward distortion in price is more likely when sellers put a higher weight on the second period profit and hence have higher incentives to prevent entry, that is, when δ is high. Hence, the profit of the platform can be the lowest under targeted entry if both r and δ are large enough. The platform's preferred entry mode is summarized in Fig. 2.

[19] The proof is straightforward and hence omitted.

5.3. Consumers

Clearly, consumers are hurt in the first period when the platform uses more individualized information in determining its entry strategy, resulting in higher prices. Under proportional fee, consumers are hurt not only because of this but also in the second period due to relaxed competition. The competition between a seller and the platform is less intense than that between two independent sellers, as the platform internalizes partially the profit of the seller via the commission fee. This competition relaxing effect is stronger when the platform sells the strong product, which has a larger impact on consumer surplus. Hence, we have:[20]

Proposition 7. *Consumer surplus can be ranked, from highest to lowest, as no entry, random entry, category entry, and targeted entry.*

6. Two extensions

6.1. Generalization to many sellers

Suppose there are n sellers in each category $i = A, B$, and the utility function of a representative consumer for products in category i is given by:

$$U = \sum_{j=1}^{n} \tilde{q}_{ij} - \frac{1}{2(1+\beta)}[2\beta \sum_{j}\sum_{k>j} \tilde{q}_{ij}\tilde{q}_{ik} + \sum_{j}(\beta + \frac{1}{w_{ij}})(\tilde{q}_{ij})^2], \tag{6}$$

where $\tilde{q}_{ij}$ is the consumption of product j in category i, w_{ij} is the strength of product j in category i with $\sum_{j=1}^{n} w_{ij} = 1$, and as before β is the degree of product differentiation. This generates a demand for product j, given by:

$$q_{ij} = \epsilon_i w_{ij}[(1 + \beta(1 - w_{ij}))(1 - p_{ij}) - \beta \sum_{k \neq j} w_{ik}(1 - p_{ik})].$$

We assume that each product j is equally likely to be the only strong product with $w_{ij} = w$, otherwise it is a weak product with a strength $w_{ij} = \frac{1-w}{n-1}$, with $w \in (\frac{1}{n}, 1]$. We maintain the other assumptions in the two sellers case.

Consider a seller in either category, let $\pi(w, r; \tilde{p}, p^e; n)$ and $\pi(1-w, r; \tilde{p}, p^e; n)$ be the first period profit when it is the strong seller and one of the weak sellers respectively, if it charges a price of $\tilde{p}$ while other sellers charge p^e. In the second period, if the platform does not enter this category, we denote the corresponding profits for the strong seller and each weak seller by $\pi^N(w, n)$ and $\pi^N(1-w, n)$. If the platform enters this category and replaces the strong seller, we denote the profit for each remaining weak seller by $\pi_S^s(1-w, n)$. If the platform enters and replaces one weak seller, we denote the profits for the strong seller and each remaining weak seller by $\pi_S^w(w, n)$ and $\pi_S^w(1-w, n)$.

Following similar steps as Lemma 1–3, we can show that the first period equilibrium prices $p_n^l, l \in \{N, C, T\}$ satisfy:

$$\int_0^{\bar{e}} \epsilon_A \frac{\pi_p(w, r; p_n^l, p_n^l; n) + (n-1)\pi_p(1-w, r; p_n^l, p_n^l; n)}{n} + \frac{\delta \epsilon_A f(\epsilon_A)}{n(1-p_n^l)} M_n^l(w, r) dF(\epsilon_A) = 0,$$

where $M_n^N(w, r) = 0$ in the case of no information usage ($l = N$),

$$M_n^C(w, r) = w[\pi^N(w, n) - \frac{n-1}{n}\pi_S^w(w, n)] + (1-w)[\pi^N(1-w, n) - \frac{1}{n}\pi_S^s(1-w, n) - \frac{n-2}{n}\pi_S^w(1-w, n)]$$

in the case of category information usage ($l = C$), and

$$M_n^T(w, r) = (1 + \beta(1-w))\pi^N(w, n) - \beta(1-w)[\pi^N(1-w, n) - \pi_S^s(1-w, n)]$$

in the case of individual information usage ($l = T$). Similar arguments as Proposition 1 imply that $M_n^C(w, r) > 0$ if r is not too large.[21] Furthermore, we have:

$$\begin{aligned} &M_n^T(w, r) - M_n^C(w, r) \\ &= (1+\beta)(1-w)[\pi^N(w, n) - \pi^N(1-w, n)] + \beta(1-w)\pi_S^s(1-w, n) \\ &+ w\frac{n-1}{n}\pi_S^w(w, n) + (1-w)[\frac{1}{n}\pi_S^s(1-w, n) + \frac{n-2}{n}\pi_S^w(1-w, n)] \\ &> 0. \end{aligned}$$

That is, the strategic pricing incentives are still at work and prices are higher with more individualized information usage, although the absolute effect is weaker, as each seller has a smaller influence on category sales under category entry or on the sales of the top seller under targeted entry.

6.2. Product differentiation between the platform and sellers

Our analysis assumes that the platform replaces the original seller when it enters, our main insights continue to hold in less extreme cases when the platform enters with a product that is a closer substitute for one seller but it does not crowd out this seller completely. We consider an example with two sellers in each category as in our main model under proportional fee. If the platform enters with a product that directly competes against seller ij with strength w_{ij}, we assume that the platform's product obtains a strength of αw_{ij} while seller ij retains a strength of $(1-\alpha)w_{ij}$, where $\alpha \in [0, 1]$. Our main model corresponds to the case of $\alpha = 1$. For example, if the platform enters category i and competes against seller $i1$, which turns out to be the strong seller, we can derive the demands for the three sellers using the utility function as (6), given by:

$$\begin{aligned} q_{i1} &= \epsilon_i(1-\alpha)w(1 - p_{i1} + \beta(1-w)(p_{i2} - p_{i1}) + \beta\alpha w(p_I - p_{i1})), \\ q_{i2} &= \epsilon_i(1-w)(1 - p_{i2} + \beta(1-\alpha)w(p_{i1} - p_{i2})) + \beta\alpha w(p_I - p_{i2})), \\ q_I &= \epsilon_i\alpha w(1 - p_I + \beta(1-\alpha)w(p_{i1} - p_I) + \beta(1-w)(p_{i2} - p_I)). \end{aligned}$$

The three sellers then compete in prices, and we denote the corresponding profits of the strong seller and the weak seller by $\pi_S^s(w)$ and $\pi_S^s(1-w)$, respectively. Similarly, we denote the profits of the strong seller and the weak seller by $\pi_S^w(w)$ and $\pi_S^w(1-w)$, when the platform enters and competes directly against the weak seller.

Following similar steps as in the main model, we can show that the equilibrium prices under category entry and targeted entry satisfy similar conditions as Eqs. (4) and (5), with $M^C(w, r)$ and $M^T(w, r)$ replaced by:

$$\begin{aligned} M_\alpha^C(w, r) &= w(\pi^N(w, r) - \frac{1}{2}(\pi_S^s(w) + \pi_S^w(w))) \\ &+ (1-w)(\pi^N(1-w, r) - \frac{1}{2}(\pi_S^s(1-w) + \pi_S^w(1-w))), \end{aligned}$$

and

$$\begin{aligned} M_\alpha^T(w, r) &= (1 + \beta(1-w))(\pi^N(w, r) - \pi_S^s(w)) \\ &- \beta(1-w)(\pi^N(1-w, r) - \pi_S^s(1-w)). \end{aligned}$$

[20] The proof for this result is straightforward and hence omitted.

[21] Since each seller is less likely to be replaced in the case of category entry, we need a lower r for this to hold.

$M^C_\alpha(w,r)$ is always positive for any $\alpha > 0$, as platform entry intensifies competition and reduces sellers' profits and market shares. Furthermore, we have:

$$M^T_\alpha(w,r) - M^C_\alpha(w,r) = (1+\beta)(1-w)\underbrace{[\pi^N(w,r) - \pi^s_S(w) - (\pi^N(1-w,r) - \pi^s_S(1-w))]}_{A(w,\alpha)} + (w - \frac{1}{2})\underbrace{(\pi^w_S(w) - \pi^s_S(w))}_{B(w,\alpha)} + \frac{1-w}{2}\underbrace{(\pi^w_S(1-w) + \pi^w_S(w) - \pi^s_S(w) - \pi^s_S(1-w))}_{C(w,\alpha)}.$$

We can show that $A(w,\alpha)$ is positive because when the platform enters and competes directly against the strong seller, it hurts the strong seller more than the weak seller. Moreover, we can show that $B(w,\alpha) > 0$ and $C(w,\alpha) > 0$ because when the platform enters and competes directly against the weak seller, it hurts the strong seller less (so $B(w,\alpha) > 0$) and it also hurts the total profits of the two sellers less than when it competes directly against the strong seller (so $C(w,\alpha) > 0$). Together with $w > 1/2$, this means that $M^T_\alpha(w,r) - M^C_\alpha(w,r) > 0$.

Hence, the strategic pricing incentives remain the same, although the overall impact on sellers now looks similar to the case of platform entry under per unit fee (See Online Appendix). Sellers are hurt whenever the platform enters under per unit fee, as the platform does not pay the per unit fee and hence is a more efficient competitor. Instead, under proportional fee, the remaining seller benefits from the platform's entry when the other seller is completely replaced. When both sellers remain to compete with the platform, the market remains competitive and both sellers could be hurt if α is not too large (so the platform does not crowd out the original seller too much), which makes the situation similar to that under per unit fee. Consequently, sellers would generally prefer no entry at all, but they would still prefer targeted entry when competition is intense and entry is inevitable.

7. Further discussions and concluding remarks

In summary, we have considered the impact of a platform's entry on competition between independent sellers, when the platform can base its entry decision on different sets of information. We show that the use of more individualized information enhances sellers' incentives to manipulate sales to influence the platform's entry strategy, which relaxes ex ante competition between sellers. Our analysis generates new insights into the ongoing discussion about the dual role of platforms as an intermediary and a seller by taking into account different extents to which data is used. In this section, we further discuss some advantages and limitations of our approach, identify several important directions for future research, and conclude with some managerial and regulatory implications of our results.

7.1. Further discussions about the model

7.1.1. Sellers' informational advantage

In our model, sellers do not know the strength of their products or the market size in the first period and learn about it afterwards. This reflects the role platforms play in facilitating sellers' experimentation with new products, some of which may turn out to be popular and some may not. This also allows us to analyze the symmetric equilibrium and obtain clear and meaningful results regarding the impact of the platform's information usage on the strategic interaction among sellers.

If sellers know the strength of their products or the market size and hence have an informational advantage over the platform, the analysis will become more complicated in two ways. Firstly, we no longer have a symmetric equilibrium in the first period, as the strong seller and the weak seller would charge different prices, determined by two non-linear equations. Yet, our main insights regarding the impact of information usage on prices would largely carry through. Specifically, comparing targeted entry to category entry under proportional fee, the deaveraging effect and the replacement effect continue to apply for the strong seller, which means the strong seller tends to set a higher price. The replacement effect and the entry easing effect continue to apply for the weak seller, which means the weak seller may set a higher or a lower price. Overall, when w is large and/or β is small, prices of both the strong and the weak sellers are higher; when w is small and/or β is large, the strong seller charges a higher price, whereas the weak seller charges a lower price. Secondly, sellers may have incentives to signal their private information about market size as studied by Jiang et al. (2011) and Li et al. (2014), which would further push up prices as shown in this strand of literature. A full analysis with asymmetric sellers and asymmetric information is beyond the scope of this article but could be an interesting avenue for future research.

7.1.2. Multiple periods and strategic sellers

To deliver our main insights, we have adopted a two-period model with forward-looking sellers. The two-period setup has the advantage of tractability and clearly demonstrating the underlying driving forces. However, to ensure equilibrium existence, we need to put restrictions on the relative length of the learning stage and the competition stage. While this is common in the literature which often assumes $\delta \leq 1$, it imposes rigidity on the modeling. With a multi-period or a continuous-time model, we would be able to model learning by the platform more flexibly and investigate other interesting issues such as how the speed of learning affects independent sellers. In such more complex setups, we believe the strategic incentives to manipulate sales still exist so as to delay or distort learning and entry by the platform. We leave the study of these models to future research, which may generate richer dynamics and deepen our understanding of information, imitation and competition in platform markets.

It would also be interesting to introduce sellers that differ in their strategic aims and study how competition among them is influenced by the platform's strategy. Our setup considers only forward-looking sellers. While this applies well to sellers that have established the platform as their main retailing channel and are aware of the strategies adopted by the platform, there could exist other sellers that are less experienced or more focused on short-term profits. This introduces additional layers of strategic considerations that sellers need to take into account, which may generate new insights into the impact on different types of sellers.

7.1.3. Non-price competition

We have focused on sellers that compete in prices. To reduce the likelihood of platform entry, sellers manipulate sales by raising their prices, which softens competition and could benefit them in some cases. Similar insights apply when sellers compete by, for example, providing valuable services to customers. In such a scenario, competition tends to result in over-provision of these services, as sellers fight fiercely for market shares. With the possibility of the platform entering based on sales information, sellers have incentives to manipulate sales and prevent platform entry by reducing these services. This again relaxes competition among sellers and may benefit them. This is in line with the analysis of Jiang et al. (2011), who show that, in a setup with a single seller, the seller may reduce valuable services when it has private information on demand. However, if sellers compete in multiple dimensions, in addition to collecting information about a single variable (sales) at different levels of granularity, the platform may have incentives to collect information about other variables (such as inventory data, marketing efforts and customers reviews) to learn about the most popular products. This points to a new and potentially fruitful direction for future research. Furthermore, sellers may invest and compete in innovation and experimentation of products. It would be interesting to investigate how information usage by the platform affects the intensity and diversity of experimentation by independent sellers.[22]

7.1.4. Competing platforms

Our analysis proceeds with a single platform. When there are multiple platforms, our analysis continues to apply for each individual platform, and it has further implications on competition between platforms. As we have seen, sellers may benefit from a platform's information usage. In these cases, the platform that uses more individualized information may attract these strategic sellers. However, other sellers, who focus more on short-term profits, may be turned away by such a strategy. Therefore, a platform needs to carefully design its information strategy, which not only affects how sellers compete when they have joined the platform but also whether and which platform they decide to join at the beginning. A thorough analysis along this direction is beyond the scope of this article but would be an important topic for future research.

7.1.5. Entry by other independent sellers

Finally, we have focused on the entry by the platform, mainly to relate our insights to the discussion surrounding the behavior of large trading platforms. Our analysis can be adapted to study the entry by other independent sellers, who rely on the information provided by the platform. Similar to our main analysis, more individualized information allows independent entrants to target the more popular products. Hence, the incentives to manipulate sales by existing sellers to prevent entry by other independent sellers are still present, and the main insights remain valid. That is, existing sellers compete less intensely and may gain when the platform provides more individualized information to potential independent entrants. However, compared to the platform, independent entrants do not internalize the profits of existing sellers via commission fees, which makes them tougher competitors in the second period. This means that, competition in the second stage tends to be more intense, which leads to lower profits for existing sellers and a higher consumer surplus. Consequently, the overall impacts of information usage on consumers and sellers become similar to the case of a per unit fee (See Online Appendix).

7.2. Concluding remarks

7.2.1. Managerial implications

For the sellers, our results show that they may actually benefit from more individualized information usage by the platform, taking into consideration how sellers could respond strategically prior to the platform's entry. Thus, in addition to adjusting selling strategies after the platform's entry, sellers should consider how to reshape their competitive strategies anticipating that the platform can use different information strategies upon entry.

For the platform, our results show that it is generally beneficial to use more individualized information under proportional fee when sellers compete fiercely, but not under per unit fee. Hence, when adopting an information usage scheme, it is important to consider sellers' strategic responses to the use of information and the structure of fees under agency selling.

[22] See, for example, Lam & Liu (2022).

7.2.2. Regulatory implications

Our results shed light on the policy discussion surrounding digital giants, especially how they might abuse their market positions by collecting and analyzing independent sellers' data. We highlight the importance of market dynamics and demonstrate the significance of considering the impacts of regulation on ex ante competition in addition to its impacts on ex post competition. In particular, potential intervention on the use of sellers' information should take into account the level and structure of commission fees and the intensity of competition among sellers. For example, under proportional fee, we show that restricting usage of individualized information could hurt both the platform and sellers but benefit consumers. However, under per unit fee, such a restriction may benefit the consumers and the platform but hurt sellers when competition between sellers is intense.

Another commonly proposed regulation to deal with the dual role of platforms as an intermediary and a trading party is to separate the two roles. In our set-up, this could be a financial break-up where the product team of the platform does not take into account the commission fees when setting the prices, or a physical break-up where the product team acts independently from the intermediary. In either case, the product team becomes similar to an independent seller. As discussed above, our main insights that more individualized information usage softens competition among sellers are still valid and our analysis continues to apply in this scenario.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2022.12.026

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