Information Sharing on Retail Platforms

(Authors' names blinded for peer review)

Problem Definition: This paper studies the information sharing strategy for a retail platform on which multiple competing sellers distribute their products.

Academic/Practical Relevance: Due to the rapid growth of retail platforms in recent years, information sharing has become an increasingly important issue because retail platforms can gather an enormous amount of consumer information that may not be visible to the sellers. Understanding how to share such information with those sellers will provide useful implications from both the theoretical and practical perspectives.

Methodology: We develop a game-theoretic model where multiple sellers engage in Cournot competition on a retail platform by selling substitutable products, and the platform charges a commission fee for each transaction. The platform owns superior demand information and can control the accuracy level when sharing the information with the sellers.

Results: We find that the platform has incentives to share the information, and such sharing is beneficial both to the platform and to all sellers. Under the asymmetric information sharing format, the optimal strategy for the platform is to select a subgroup of sellers and *truthfully* share information with them. Under the symmetric sharing format, the platform must share the same information with all sellers and thus has incentives to reduce the accuracy of the shared information. Moreover, we identify a simple pricing mechanism that can achieve the optimal information sharing outcome.

Managerial Implications: This research highlights the importance of considering the impact of information sharing for a retail platform with competing sellers. It also proposes a simple, single-price mechanism to implement the optimal sharing strategy. These results could provide useful guidelines for platform managers to better design their information sharing services.

Key words: Information sharing; retail platform; pricing mechanism; platform operations

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1. Introduction

"Platforms are eating the world". Parker et al. (2016) brought up the slogan as an update to Netscape founder Marc Andreessen's vision: "Software is eating the world". They think the new omnivore is really "the platform": the digitized, open, and participative business models creating

commercially connected ecosystems of producers and consumers (Manville 2016). In the world of platforms, the Internet no longer acts merely as a distributional channel, but also as a creation infrastructure and a coordination mechanism. Retail business is among the earliest industries to take advantage of the power of the platform. For example, Alibaba Group is a Chinese online retail platform whose Gross Merchandise Value (GMV) has surpassed 485 billion U.S. dollars (USD) as of 2016.[1] This makes Alibaba the world's largest retailer, overtaking Walmart, which posted revenues of 482.1 billion USD for the same year.[2]

Compared to the traditional brick-and-mortar retailers, online retail platforms are able to gather more information from customers' engagement and virtual footprint, such as customer browsing history, on top of the traditional sales data. Since customers usually interact directly with the platform's website or mobile app, such data may not be visible to each individual seller, which means platforms own more information about customers than sellers. For example, in addition to the sales information, retail platforms often own the clickstream data of each seller, which the sellers may not be able to observe. The clickstream data often includes how many customers searched or viewed a particular product. It may also include how many people viewed and clicked through the advertisement of the product. Another example could be each seller's competitors' data. For instance, the platform knows how many customers viewed/visited/searched/purchased on a seller's competitors' sites while this focal seller does not know.

This additional information can help the sellers make better operations decisions. The literature has proven in multiple settings that clickstream data is useful in predicting consumers' purchasing behavior on top of the sales data and, in turn, making better operations decisions, such as inventory replenishment or pricing. For example, Moe and Fader (2004) use session-level web browsing data to better predict consumers' purchasing behavior. Likewise, Montgomery et al. (2004) predict consumers' online purchasing conversion more accurately by analyzing the page-by-page viewings

[1] http://www.alibabagroup.com/en/news/presstextunderscore pdf/p160505.pdf

[2] https://www.forbes.com/sites/jlim/2016/05/05/alibaba-fy2016-revenue-jumps-33-ebitda-up-28/#5f15a05f53b2

of a visitor through the path data. Huang and Van Mieghem (2014) show that clickstream data is useful in demand forecasting and can help the firm make better replenishment decisions. Moreover, competitors' data are also very useful in predicting market demand. One of the major operations decisions of e-commerce platforms, such as Alibaba, is to match products to each individual customer, a system often referred to as a recommender system. When building such a recommender system, those platforms often utilize data from many sellers to forecast the demand from a particular customer for a particular product. For example, Feldman et al. (2018) document that Alibaba uses data from all sellers when designing the recommendation engine. This means that, even for forecasting a particular customer's demand for a specific product, knowing the data from all sellers would greatly help to enhance accuracy.

A natural question for the platform is whether and how to share her proprietary information with the sellers. In practice, retail platforms surely understand the value of such information. In fact, some retail platforms have started experimenting with various information sharing services. For example, Business Advisor (Sheng Yi Can Mou), the data analysis tool provided by Alibaba to the sellers, shares with each seller his clickstream data as well as his competitors' information.

Despite the fact that practitioners have experimented with various information sharing strategies, there is little research about the optimal way for a retail platform to share information with sellers. Haphazard information sharing may intensify competition and cause undesired outcomes, which can be detrimental to both the sellers and the platform. Therefore, it is crucial to understand the impact of information sharing between the platform and the sellers and characterize the optimal information sharing strategy for the platform.

To obtain a better understanding of the above questions, we develop a game-theoretic model where multiple sellers distribute substitutable products through an online retail platform and engage in Cournot competition. The sellers face a common demand uncertainty in the market and have their own prior beliefs about the demand uncertainty. The platform can collect demand signals based on customer interaction data that are not observable to the sellers. In our model, the

platform engages in revenue-sharing contracts with the sellers, and her objective is to maximize her expected profit by deciding whether and how to share information with each individual seller.

Specifically, we focus on the case where the platform is the owner of the information and can determine the sharing strategy, in contrast with individual ownership of the information (e.g., Gal-Or 1985). Together with the change of information ownership, the platform's objective to maximize the total profit of all sellers leads to a different sharing outcome. It allows the platform to utilize the information while mitigating the competition level, which is not viable when an individual seller owns the information. We find that information sharing is beneficial to both the platform and the sellers. In other words, a profit-maximizing platform has incentives to share information with the sellers. However, it may not be optimal to share all information with every seller. The major trade-off is between the increased utilization of the information and the intensification of competition as a result of information sharing. On one hand, sharing more information provides knowledge the sellers can use to increase their profits. On the other hand, sharing too much information results in a higher correlation among sellers' strategies, and therefore intensifies the competition among sellers and drives down their profits. To mitigate competition intensity, the platform can either limit the number of sellers who receive the information, or lower the precision of the information shared. Our model shows that limiting the sharing group size is more efficient than lowering the precision of information. In particular, the optimal sharing strategy for the platform, without any constraints, is to limit the sharing group size and truthfully share the information with every seller in the group.

Meanwhile, the platform may not be able to share information arbitrarily due to potential practical concerns. One commonly encountered issue for the platform in sharing information is the privacy of sellers. The misuse of sellers' individual information can cause very serious brand damage and financial loss to the platform. For example, Facebook's stock dropped 5% after it was discovered that Cambridge Analytica was misusing users' information on Facebook (see Shen 2018). Another important issue for the platform is fairness. Platforms that favor certain sellers will

face serious public relations problems or even government regulation pressure. Therefore, ensuring that platforms treat sellers fairly is crucial.

In our model, the platform can either share with sellers full information based on the customer interaction with all sellers or individual information based on the customer interaction with each individual seller only, possibly with noises. When privacy is a constraint, the platform is not allowed to share one seller's individual information with other sellers. Under fairness constraint, the platform's sharing strategy must be symmetric: Either all sellers receive the full information with the same precision levels or each seller receives his own individual information with the same precision levels across sellers. Therefore, we study four types of information sharing formats: *Asymmetric Full Sharing (AFS)*, *Asymmetric Individual Sharing (AIS)*, *Symmetric Full Sharing (SFS)*, and *Symmetric Individual Sharing (SIS)*.

By characterizing the optimal sharing strategies under these four sharing formats, we first establish that both the platform and the sellers can be better off with information sharing even with the above constraints. When the sharing strategy can be asymmetric, we find that the optimal strategy for the platform is to choose a subset of sellers and truthfully share information with them. When the sharing strategy has to be symmetric, the platform will reduce competition by lowering the precision of the shared information, which generates lower profit for the platform compared to the unconstrained case. Moreover, we propose a simple pricing mechanism that can implement the optimal sharing strategy. Under this mechanism, the platform charges a fixed price for the information, and this pricing mechanism will induce a subset of sellers to purchase the information. Even if the sellers are homogeneous, only a subset of sellers will purchase the information at a fixed price because, as the number of sellers who own the information increases, the value of the information will decrease. The platform can adjust the price level so that the number of sellers who purchase the information in the equilibrium is equal to the optimal number of sellers to share information with. In this case, the fixed-price mechanism will achieve the first-best information sharing outcome.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces the model and information sharing structure. Section 4 derives the optimal information sharing strategy and examines how it depends on the privacy constraint, and Section 5 analyzes the sharing strategy with the fairness constraint. Section 6 characterizes the optimal pricing mechanism. The paper concludes with Section 7.

2. Literature Review

This paper is related to the extensive literature on information sharing in operations management (e.g., Ha et al. 2011, Chen and Tang 2015, Tang et al. 2015, Liao and Chen 2017, Liao et al. 2017, He et al. 2018) and economics (e.g., Vives 1984, Gal-Or 1985, 1986, Raith 1996). The majority of studies in economics literature focus on investigating the incentive and impact of information sharing with horizontal competition among oligopolies. A key message from theses studies is that the sellers who participate in Cournot competition by selling substitutable products will not share demand information in the equilibrium. Several studies investigate vertical information sharing, where a supplier shares information with retailers involved in horizontal competition (Li 2002, Zhang 2002, 2006, Shang et al. 2015). Recently, researchers also investigate the impact of information sharing from a third party that is not related to sellers. For instance, Jensen (2007) finds that information sharing of market price via mobile devices in South India helped to increase the fishermen's profit and reduce waste. Chen and Tang (2015) and Tang et al. (2015) investigate the effects of full information sharing on farmers' welfare in developing countries. Another related stream of research studies information design questions using a Bayesian persuasion framework; please see Bergemann and Morris (2019) for a review of this literature.

Our research contributes to the above literature by bridging the information sharing literature with the recent practice of rapidly growing retail platforms. Our model is different from the above studies both in the information structure (i.e., it is the platform rather than the sellers who own the information) and in the decision structure (i.e., it is the platform rather than the sellers who make the information sharing decision, and the objective is to maximize the sellers' total profits

rather than individual seller's profit). We find that in contrast to the classic literature (Gal-Or 1985, Raith 1996) that predicts no information sharing in equilibrium, the platform has incentives to share information with the sellers. Our analysis also reveals that it is the new decision structure that drives such a distinct finding. This indicates that the platform serves as an informational intermediary that facilitates information sharing in our setting.

Moreover, we consider two new but practically important constraints, i.e., the privacy and fairness constraints, in information sharing that are not discussed in the traditional literature. We characterize the optimal information sharing strategies under these two constraints. Since the platform owns the information and makes the sharing decision, it is natural to consider whether there are any contracts between the platform and sellers that could implement the optimal information sharing strategy in equilibrium. Therefore, unlike most past literature that only characterizes the optimal information sharing strategy, we propose an implementable pricing mechanism that achieves the optimal sharing outcome.

There is a substantial literature on information privacy, specifically in e-commerce contexts (see Malhotra et al. 2004, Son and Kim 2008, Pavlou 2011, Li 2012, Easley et al. 2018). We consider a situation where sharing one seller's information with another may violate the privacy constraint. Moreover, there is a related literature on fairness in pricing and resource allocation (e.g., Bertsimas et al. 2011, 2012). Bertsimas et al. (2012) study how to design objectives that account for the trade-off between fairness and efficiency in the context of resource allocation problems. In this paper, we apply the concept of fairness to information sharing and pricing of information.

This paper is also related to the recent literature on retail platforms. For instance, Jiang et al. (2011) discuss the firms' strategies in platform-based retailing when the platform may directly compete with sellers. Hagiu and Wright (2014) focus on the strategic choice between the platform scheme (agency) and the wholesale scheme (re-seller). By conducting a large randomized field experiment on Alibaba, Zhang et al. (2019a) investigate the effect of price promotion on customer behavior and Zhang et al. (2019b) study the value of pop-up stores on retail platforms. Our

paper contributes to this literature by focusing on one under-explored but practically important information design question in platform retailing.

Besides information sharing on retail platforms, the recent operations management literature also features papers studying other important operational issues on platforms. Cachon et al. (2017), Hu and Zhou (2017), Taylor (2018), and Cui and Hu (2018) study optimal pricing in on-demand service platforms. Hu and Zhou (2017), Cullen and Farronato (2014), Kanoria and Saban (2017), Özkan and Ward (2020), and Li and Netessine (2020) explore the matching processes on a platform. Cui et al. (2020) and Edelman et al. (2017) examine the discrimination issue on the lodging platform, Airbnb. Jin et al. (2017) and Fradkin et al. (2017) focus on the review system on a platform. Benjaafar et al. (2018) and Horton and Zeckhauser (2016) study the implications of rental platforms for consumers' ownership of durable goods. These papers do not consider information sharing, and therefore both the modeling and insights are quite different from our paper.

3. Model Setting

In this section, we first introduce the model setting and the information sharing problem for the platform. Then we describe the information sharing formats that we will study in the subsequent sections.

3.1. Platform's Information Sharing Problem

Consider N sellers distributing substitutable products on a retail platform. The platform takes a fixed percentage of each seller's revenue as a commission fee.[3] The sellers participate in Cournot competition and have to make quantity decisions to maximize their expected profit before the common market uncertainty is resolved.[4] Specifically, given all sellers' quantity decisions q_i, $i =$

[3] Revenue-sharing contracts between platform and sellers are very common in practice. For instance, both Tmall.com (i.e., Alibaba) and Amazon charge a fixed percentage of the revenue generated through the platform as a commission fee, and the commission rate can vary based on the product category.

[4] We follow the classic information sharing literature to adopt Cournot competition. In Appendix A, we show that similar to Raith (1996), our main results continue to hold under Bertrand competition with complementary products.

$1, 2, \ldots, N$, the price of the product sold by seller i is represented by a linear inverse demand function:

$$p_i = a - q_i - b \sum_{d \neq i} q_d + u, \quad \forall i \in \{1, 2, \ldots, N\}, \tag{1}$$

where a and b are parameters that are known by all sellers, and u is a random term that represents the common market demand uncertainty.

Following the literature on Cournot competition (Sakai and Yamato 1989, Ha et al. 2011, 2017), we assume $0 < b \leq 1$, where $b > 0$ indicates that the products are substitutes. When $b < 1$, one seller's quantity decision has a greater effect on the price of his own product than other sellers' quantity decisions. The closer to 1 the coefficient b is, the more substituitable the products are. In particular, when $b = 1$ all sellers in the market are selling perfectly substituitable products. Note that the substitution rate b is the same between any pair of the sellers in the base model, i.e., the sellers are homogeneous in terms of market power. In Appendix B, we analyze an extension where sellers have heterogeneous market power and find that the key results remain the same.

Similarly, following the literature on information sharing (Raith 1996, Mendelson and Tunca 2007, Feldman et al. 2018), we assume u follows a normal distribution known to both the platform and the sellers. Without loss of generality, we normalize the mean of the distribution to zero: $u \sim N(0, \sigma)$. The platform has superior information about the market demand than each seller. Specifically, the sellers' information about the demand uncertainty is the prior distribution of the uncertain term u. The platform, in addition to the prior distribution, can also obtain signals of the market demand uncertainty based on customer-seller interactions, such as the customers' clickstream data. Denote the signal from the customer interaction with seller i as x_i, which is a noisy but unbiased estimate of the market demand uncertainty u:

$$x_i = u + e_i, \quad \forall i \in \{1, 2, \ldots, N\}.$$

Here e_i is a normally distributed random noise with mean 0. In particular, we assume that the noises of these individual signals are independent from each other and the market uncertainty: $e_i \sim N(0, t)$, $\forall i$, $cov(e_i, u) = 0$, $\forall i$ and $cov(e_i, e_j) = 0$, $\forall i \neq j \in \{1, 2, \ldots, N\}$.

Let $\{x_1, x_2, \ldots, x_N\}$ denote the information set possessed by the platform. The sellers can learn extra information about the market only through the platform, and the platform has to decide how to release these signals to the sellers.[5] In other words, the platform determines the information sharing strategy — what signals to be revealed, to which seller, and at what accuracy level. Any information sharing strategy can be represented as a set of noises added to each signal before sharing it with each seller. Specifically, the platform shares information $\hat{x}_{ij}$ to seller j about the signal x_i from customer interaction data with seller i in the following way:

$$\hat{x}_{ij} = x_i + \epsilon_{ij}, \forall i, j = 1, 2, \ldots, N, \qquad \epsilon_{ij} \sim N(0, m_{ij}), \forall i, j,$$

$$cov(\epsilon_{ij}, x_k) = 0, \forall i, j, k, \qquad cov(\epsilon_{i_1 j_1}, \epsilon_{i_2 j_2}) = 0, \forall i_1 \neq i_2 \text{ or } j_1 \neq j_2.$$

where ϵ_{ij} is the random noise that the platform adds to the original signal x_i before sharing it with seller j, and m_{ij} is the chosen noise level for the shared information. Notice that we follow the literature (Gal-Or 1985) to assume normal noise and use normal-normal prior-posterior distribution pair to model our information structure.

The platform can determine the precision of shared information by controlling the variances of the noises, i.e., m_{ij}. When $m_{ij} = 0$, it means that the platform reveals signal x_i truthfully to seller j. When $m_{ij} = +\infty$, it means that the platform does not share any information of x_i with seller j.[6] The shared information $\hat{x}_{ij}$ with $0 \leq m_{ij} < +\infty$ will help the seller j to obtain a better estimation of the market uncertainty. Following the past literature on information sharing (Gal-Or 1985, Li 2002, Liao et al. 2017), we assume that the noises are random and independent from each other and the original signals.

As in Gal-Or (1985), the shared information can be viewed as an unbiased estimator of the demand uncertainty term u. In practice, the platform can adjust the accuracy of shared information by either only sharing a subset of available information or by controlling the detail level of the revealed information.

[5] In Appendix C, we show that our main results are robust when sellers can learn from their own private information.

[6] We follow Gal-Or (1985) to interpret an infinite noise variance as not sharing any information.

Table 1 Summary of Notation

N	Number of sellers on the platform. Seller $i \in \{1, 2, \ldots, N\}$.
q_i	Selling quantity decision of seller i.
p_i	Price of seller i's product.
a	Intercept of the inverse demand function.
b	Substitution parameter.
u	Random term in demand, $E[u] = 0$.
x_i	Signal induced by customers' interaction with seller i about the market uncertainty.
e_i	Noise term in signal x_i; $x_i = u + e_i$.
t	Variance of noise term e_i; $e_i \sim N(0, t)$.
$\hat{x}_{ij}$	Information shared by platform with seller j based on x_i.
ϵ_{ij}	Noise added by the platform to x_i to share with seller j; $\hat{x}_{ij} = x_i + \epsilon_{ij}$.
m_{ij}	Variance of the noise added to signal x_{ij} that is provided to sellers j; $\epsilon_{ij} \sim N(0, m_{ij})$.
M	Information precision matrix. $M = (m_{ij})_{N \times N}$.
y_i	Information provided by the platform to seller i.
π_i	Expected profit of seller i.
Π	Expected profit of the platform.

Let $M = (m_{ij})_{N \times N}$ denote the precision matrix. By adjusting M, the platform can choose how precise the signals should be and with whom to share the information. Therefore, any sharing strategy can be determined by a particular precision matrix M. Let $y_i(M)$ represent the information shared by the platform with seller i. We then denote the shared information received by seller i as $y_i(M) = \{\hat{x}_{1i}(m_{1i}), \ldots, \hat{x}_{Ni}(m_{Ni})\}$.

Upon receiving the shared information $y_i(M)$ from the platform, seller i first updates his belief about the market uncertainty u and gets $u|y_i(M)$. Based on his belief of the market, seller i then makes the quantity decision q_i to maximize the expected profit:

$$\pi_i(q_i) = E\left\{(1-\alpha)q_i p_i \middle| y_i(M)\right\} = E\left\{(1-\alpha)q_i\left(a - q_i - b\sum_{d \neq i} E\left[q_d|y_i(M)\right] + E[u|y_i(M)]\right)\right\}, \quad (2)$$

where α is the commission rate under the revenue-sharing contract. Using the posterior distribution u, we have

$$E[u|y_i(M)] = \sum_{j=1}^{N} \frac{\frac{1}{t+m_{ji}}}{\frac{1}{\sigma} + \sum_{d=1}^{N} \frac{1}{t+m_{di}}} \hat{x}_{ji}(m_{ji}). \quad (3)$$

Since π_i is concave in q_i, the optimal quantity for seller i can be calculated from the first-order condition:

$$q_i^*(y_i(M)) = \frac{1}{2}\left(a - b\sum_{d \neq i} E\left[q_d|y_i(M)\right] + E[u|y_i(M)]\right). \quad (4)$$

Consequently, the equilibrium of production quantities for all sellers can be derived from Equation (4).

We consider a revenue-sharing contract under which the platform takes α fraction of the revenue from sellers as commission fees.[7] Normally, α is determined by the industry standard and thus is exogenously given.[8] For example, Alibaba's Tmall platform uses different α values for different product categories. In particular, Tmall charges 5% for apparel ($\alpha_{apparel} = 0.05$) and 2% for electronics and digital products ($\alpha_{electronics} = 0.02$).[9] Moreover, for most of the categories, the commission rate does not change frequently. For instance, the commission rate for apparel has remained stable at 5% for more than six years. The platform maximizes her expected profit by determining the precision matrix M. After the platform shares $y_i(M)$ with seller i, the expected profit of the platform can be written as

$$\begin{aligned}\Pi(M) =& E\left[\sum_{i=1}^{N} \alpha q_i^*(y_i(M)) p_i^*(y_i(M)) \middle| x_1, \ldots, x_N\right] \\ =& E\left[\sum_{i=1}^{N} \alpha q_i^*(y_i(M)) \left(a - q_i^*(y_i(M)) - b\sum_{d\neq i} E\left[q_d^*(y_d)|y_i(M)\right] + E[u|y_i(M)]\right) \middle| x_1, \ldots, x_N\right].\end{aligned}$$

Sequence of Events: The platform first determines the precision matrix M. After the signals about market uncertainty based on all sellers $x_1, \ldots, x_N$ are realized, the platform shares the information $y_i(M)$ with seller i based on the pre-determined precision matrix M. Seller i uses the signals he receives to update his belief about the market and then determines quantity q_i to maximize his expected profit. Once the quantities $q_1, \ldots, q_N$ are determined, the market price of each seller's product is realized, and each seller's profit is also realized. Finally, the platform collects her commissions as a fraction of the total revenue of all sellers. Table 1 summarizes all notations in our main model.

[7] The fact that the platform owns the information and does not participate in the competition herself is crucial in determining the optimal information sharing strategy. Our model applies to situations where retail platforms do not directly compete with the sellers (e.g., Alibaba).

[8] We assume that the platform cannot jointly optimize α and her information sharing strategies since α is normally determined by industry competition and rarely changes, whereas the price and format of information sharing on a platform may be updated quite often. Nevertheless, endogenizing α would not change the qualitative results.

[9] http://about.tmall.com/tmall/fee_schedule

As a benchmark case, we document the sellers' quantity decisions in equilibrium when there is no information sharing in Lemma 1.

LEMMA 1. *When the platform does not share any information with the sellers, each seller i would produce $q_{NS,i} = \frac{a}{2+b(N-1)}$, and the platform's expected profit is $\Pi_{NS} = \frac{\alpha N a^2}{[2+b(N-1)]^2}$.*

It is worth mentioning that the sellers who do not receive information will always have the same expected profit as they do in this no-information-sharing benchmark case.

3.2. Information Sharing Formats and Constraints

In practice, the platform's sharing strategy may be subject to two potential constraints. The first constraint is privacy. Amid public concerns over Cambridge Analytica's usage of Facebook data and a subsequent movement to encourage users to abandon Facebook, there is a renewed focus on whether platforms can collect individual information and make it available to others. Improper sharing of individual information may cause significant financial losses and reputation damage. In our model, under this privacy constraint, the platform cannot release the signal based on customer interaction with one seller to his competitors, and signals obtained through customer interaction with any specific seller can only be exclusively offered to himself.

The second constraint is fairness. Fairness requires the platform to ensure that information shared with each seller is based on customer interaction data with the same set of sellers and has the same precision when the information is offered free of charge. With fairness constraint, the platform needs to treat all sellers equally in sharing information. When the platform is not obligated to be fair to all sellers, the platform has more flexibility in sharing information. For instance, the platform can offer information to some sellers but not to others. The information released to different sellers may also have different precision. In practice, millions of sellers depend on online platforms to reach their customers; therefore, ensuring that platforms treat sellers fairly is crucial from a government-regulation perspective. When the platform can charge a price for the information, fairness constraint represents providing the same pricing contract to all sellers. We first focus on the free information situation and will discuss the pricing contract in Section 6.

Based on these two constraints, we classify the information sharing strategies in two ways. First, an information sharing strategy can be *individual* and satisfy the privacy constraint, which means that only one seller's individual information can be shared with himself (i.e., $m_{ij} = +\infty \ \forall i \neq j$). The sharing strategy can also be *full*, which means the information from all sellers can be shared with every seller (the privacy constraint is violated in this case). Second, an information sharing strategy can be symmetric, which means the precision of the information is the same across all sellers, or asymmetric, in which case the fairness constraint is violated.

As a result, based on which constraint is violated, we have four types of information sharing formats. The first sharing format, denoted as *Asymmetric Full Sharing (AFS)*, allows the platform to share full information of different precisions with sellers. The second format is called *Asymmetric Individual Sharing (AIS)*, where the platform can only share one seller's individual information with himself, but the noises added to the shared signals may differ across sellers. The third and fourth sharing formats are *Symmetric Full Sharing (SFS)* and *Symmetric Individual Sharing (SIS)*, respectively. Under the *Symmetric Full Sharing* format, the platform can only share full information of the same precision with all sellers, while, under the *Symmetric Individual Sharing* format, the platform can only release one seller's individual information to himself, and the precision levels of this information must be the same across sellers. Table 2 summarizes these four sharing formats. Note that these sharing formats do not exhaust all possibilities. In particular, Table 2 does not include the case where each seller can get signals from a different set of sellers, which allows all m_{ij}'s to be different. This general sharing format is much more challenging to solve and might be overly complex for implementation in practice. In the online appendix, we show that the main results still hold for the two-seller model under the most general sharing format.

Notice that when the platform shares full information, letting $\eta_i = m_{ji}, \forall j$ and using the posterior distribution of u, we have

$$E[u|\hat{x}_{1i}(\eta_i), \ldots, \hat{x}_{Ni}(\eta_i)] = \frac{\sigma}{\sigma + \frac{t+\eta_i}{N}} \frac{1}{N} \sum_{j=1}^{N} \hat{x}_{ji}(\eta_i), \tag{5}$$

Table 2 Information Sharing Formats

	Without Fairness Constraint (Section 4)	**With Fairness Constraint (Section 5)**
Without Privacy Constraint	Asymmetric Full Sharing (AFS) $m_{i_1 j} = m_{i_2 j}, \forall i_1, i_2, j$	Symmetric Full Sharing (SFS) $m_{i_1 j_1} = m_{i_2 j_2}, \forall i_1, i_2, j_1, j_2$
With Privacy Constraint	Asymmetric Individual Sharing (AIS) $m_{ij} = +\infty, \forall i \neq j,$	Symmetric Individual Sharing (SIS) $m_{ij} = +\infty, \forall i \neq j$and $m_{ii} = m_{jj}, \forall i \neq j.$

which means, for each seller i, sharing $\{\hat{x}_{1i}(\eta_i), \ldots, \hat{x}_{Ni}(\eta_i)\}$ is equivalent to sharing $\left\{\frac{1}{N}\sum_{j=1}^{N} \hat{x}_{ji}(\eta_i)\right\}$ in our model with normal prior of normal distribution. Since we have $\frac{1}{N}\sum_{j=1}^{N} \hat{x}_{ji}(\eta_i) = \frac{1}{N}\sum_{j=1}^{N} x_j + \frac{1}{N}\sum_{j=1}^{N} \epsilon_{ji}$, the set of information y_i received by each seller serves as the aggregated information of the whole market. Therefore, sharing full information (a collection of signals from all sellers) and sharing aggregate information (the average observations from all the sellers) are equivalent in our model setting. The property that the aggregate signal is sufficient to predict the uncertainty term given the full information set will hold for a variety of interesting prior-posterior distribution pairs, including normal-normal, gamma-Poisson, and beta-binomial, according to Li (1985). At Business Advisor, both types of information are available for sellers, and we use full information to emphasize sellers' access to competing sellers' information.

When the platform shares individual information, belief updating is only based on the individual signal each seller receives and can be characterized as follows:

$$E[u|\hat{x}_{ii}(m_{ii})] = \frac{\sigma}{\sigma + t + m_i}\hat{x}_{ii}(m_{ii}). \tag{6}$$

Next, Section 4 studies the optimal sharing strategy and how the privacy constraint may change the result. Section 5 further analyzes the case when there is fairness concern.

4. Optimal Asymmetric Sharing Strategy and Privacy Concern

In this section, we study the optimal information sharing strategy under AFS and AIS formats. The following proposition characterizes the structure of the optimal asymmetric sharing strategy.

Proposition 1 **(Optimal Asymmetric Sharing Strategy)**. *In the optimal sharing strategy under the AFS and AIS formats, the platform will never partially share any information with any sellers (i.e., $m^*_{ij} \in \{0, +\infty\}$, $\forall m^*_{ij} \in M^*_{AFS}$ or M^*_{AIS}).*

All proofs are given in the online appendix. Proposition 1 shows that, under the *AFS* and *AIS* formats, the platform will always truthfully share information if she decides to share any information with any sellers. This result can be explained as follows. The platform faces a major trade-off when sharing information with sellers: On one hand, with the shared information sellers are better informed about the market, which makes them more profitable; on the other hand, in a Cournot competition framework with common demand uncertainty, information sharing increases the correlation of the sellers' strategies, which results in intensified competition and thus profit loss. We show that the platform's marginal benefit of sharing information to each seller under the *AFS* or *AIS* formats, which is defined as the benefit of better informed decisions minus the cost of more correlated strategies, is either monotonic, or first decreasing and then increasing in the noise level of shared information. Hence the optimal noise level for any seller under the *AFS* or *AIS* formats is either 0 or $+\infty$, i.e., the platform will truthfully share information if she decides to share any.

The result that the platform may truthfully share information in Proposition 1 is in contrast with the literature (Gal-Or 1985, Raith 1996), which asserts that information sharing will not arise in equilibrium. There are two important differences between our model and the traditional models: First, the information structure is different—while information is owned and submitted by each participating seller in traditional models, all shareable information belongs to the platform in our model. Second, the decision-makers and the objective functions are different—while each seller decides whether to share his own information with others to optimize his own payoff in traditional models, in our model, the platform serves as an information intermediary and maximizes the total profits of all sellers. In Appendix D, we construct an auxiliary model where the platform does not own superior information than the sellers and shows that she is still willing to share information in that model. Combining Proposition 1 with the results from Appendix D, we demonstrate that the difference in decision structure is the main driver of the difference between our result and those in the traditional models. The intuition is as follows. When each seller is the decision-maker, receiving

information from other sellers is beneficial to the focal seller due to better-informed decisions, but sharing his own information with other sellers is harmful because of more correlated strategies. Thus, each seller would have incentives to deviate from the information sharing outcome, which in turn results in a no-sharing equilibrium. However, the platform would share information as long as the benefit of more informed decisions is greater than the cost of more correlated strategies, from the system's perspective. Therefore, the platform plays an informational role that facilitates information sharing in our problem setting.

We proceed to shed more light on the platform's optimal sharing strategy under *AFS* and *AIS* formats. Although Proposition 1 shows that the platform will truthfully share information, it is not clear whether the optimal sharing strategy is symmetric or not. Proposition 2 states that the optimal *AFS* strategy is asymmetric in general — the platform shares information only with a subset of K sellers, where K is between 0 and N. Without loss of generality, we assume that, if the platform shares information with K sellers ($K \leq N$), the sellers $1, 2, \ldots, K$ receive the full information offered by the platform.

Proposition 2 **(Optimal Asymmetric Full Sharing)**. *The optimal AFS strategy is to provide the full information truthfully to K^*_{AFS} sellers:*

$$y_i(M^*_{AFS}) = \begin{cases} \{x_1, \ldots, x_N\}, & \text{if } i \leq K^*_{AFS}, \\ \emptyset, & \text{otherwise}, \end{cases}$$

where the optimal number of sellers to share is:

$$K^*_{AFS} \in \left\{ \left\lfloor \min\left\{\frac{2}{b} - 1, N\right\} \right\rfloor, \left\lceil \min\left\{\frac{2}{b} - 1, N\right\} \right\rceil \right\}.^{10} \tag{7}$$

The expected profit of the platform under this strategy is:

$$\Pi^*_{AFS} = \frac{\alpha N a^2}{[2 + b(N-1)]^2} + \frac{\alpha K^*_{AFS} \sigma^2}{[2 + b(K^*_{AFS} - 1)]^2 \left(\sigma + \frac{t}{N}\right)}. \tag{8}$$

Both the platform and the sellers can (weakly) benefit from the optimal AFS strategy compared with the no-information-sharing benchmark case.

[10] We define $\lfloor x \rfloor$ to be the greatest integer that is smaller than or equal to x and $\lceil x \rceil$ represents the smallest integer that is greater than or equal to x.

We offer the following intuition behind Proposition 2. From Proposition 1, it is optimal for the platform to truthfully share information under the *AFS* format. Therefore, we can examine how the total profits of the platform change with respect to the number of sellers she decides to share information with. It can be readily shown that the marginal benefit of sharing information to an additional seller (i.e., the benefit of better-informed decisions minus the cost of more correlated strategies due to information sharing) decreases as more sellers receive information. This is because, when more sellers have the information, the platform's benefit from better-informed decisions by this additional seller decreases. We can also show that the marginal benefit of sharing information to an additional seller is positive when no seller has such information. Combining these two facts, we know that the optimal number of sellers to share information can be any number between 0 and N. The optimal sharing strategy will be asymmetric if $0 < K < N$.

Notice that the optimal number of sellers to share with, $\min\left\{\frac{2}{b}-1, N\right\}$, may not be an integer, but we can only share with an integer number of sellers in reality. So we need to compare the expected profit at the two nearest integers around $\min\left\{\frac{2}{b}-1, N\right\}$ and pick the one that generates higher profit as the optimal number of sellers to share information with. Equation (7) shows that the number of sellers receiving information is weakly decreasing in the substitution level b and weakly increasing in the number of sellers N. As the substitution level between the sellers decreases, more sellers should be informed of the full information. In other words, more sellers should receive the information when the market is more differentiated. They can better utilize the information about the demand to increase their expected profit without affecting other sellers too much. To be more specific, in a relatively small market with few sellers, the information observed by the platform across sellers may not be precise and the competition among the sellers is not intense. In this case, $\min\left\{\frac{2}{b}-1, N\right\} = N$, and the optimal *AFS* strategy for the platform is to fully utilize the information by truthfully sharing it with all sellers. However, as the number of sellers increases, the platform can have more accurate full information and the competition among sellers is intense. In this case, $\min\left\{\frac{2}{b}-1, N\right\} = \frac{2}{b}-1 < N$, and the platform only shares full information with a subset

of sellers. Furthermore, Proposition 2 also indicates that, as long as the number of sellers is greater than $\frac{2}{b}-1$, the optimal size of sellers with shared information remains unchanged at $\frac{2}{b}-1$. When there is perfect substitution (i.e., $b=1$), $K^*_{AFS}=1$. This means that the optimal AFS strategy for the platform is to combine information from all sellers and share it with only one seller when all the products are perfectly substituitable.

Sellers who receive the information can strictly benefit from the information, and the expected profit for the others remains the same as in the case where no one gets any information. The platform, by strategically sharing information with a limited number of sellers, maximizes her own profit through collecting the commissions from all sellers.

Next, we consider the optimal AIS strategy where the platform can only share individual information with the sellers.

Proposition 3 **(Optimal Asymmetric Individual Sharing)**. *The optimal AIS strategy is to provide the individual information truthfully to K^*_{AIS} sellers:*

$$y_i(M^*_{AIS}) = \begin{cases} \{x_i\}, & \text{if } i \le K^*_{AIS}, \\ \emptyset, & \text{otherwise}, \end{cases}$$

where the optimal number of sellers to share is:

$$K^*_{AIS} \in \left\{ \left\lfloor \min\left\{ \frac{2(\sigma+t)}{b\sigma} - 1, N \right\} \right\rfloor, \left\lceil \min\left\{ \frac{2(\sigma+t)}{b\sigma} - 1, N \right\} \right\rceil \right\}. \tag{9}$$

The expected profit of the platform under this strategy is:

$$\Pi^*_{AIS} = \frac{\alpha N a^2}{[2+b(N-1)]^2} + \frac{\alpha K^*_{AIS}\sigma^2(\sigma+t)}{\left[\left(2+b(K^*_{AIS}-1)\right)\sigma+2t\right]^2}. \tag{10}$$

Both the platform and the sellers can (weakly) benefit from the optimal AIS strategy compared with the no-information-sharing benchmark case.

Similar to Proposition 2, to derive the optimal AIS strategy, we need to compare the expected profit at the nearest integers around $\min\left\{\frac{2(\sigma+t)}{b\sigma}-1, N\right\}$ and pick the one that generates higher profit as the optimal number of sellers to share information with.

Expression (9) shows that the optimal number of sellers who will receive their own individual information is weakly increasing in the seller population N and the noise level of signals t, and weakly decreasing in the substitution level b and the variance of prior beliefs σ. Moreover, when the seller population N is large enough (i.e., $N > \frac{2(\sigma+t)}{b\sigma} - 1$), Expression (9) shows that only a fixed number of sellers will receive their individual information truthfully under the optimal *AIS* strategy.

Proposition 3 implies that more sellers should receive individual information when the individual information itself is less informative about the market demand or the products sold by different sellers are more differentiated. When the individual information is not informative, sharing it with more sellers will not correlate their quantity decisions too much. Therefore, more sellers can benefit from the individual information without suffering significant losses from the higher correlation. When the products are highly differentiated, one seller's decision does not affect others' prices significantly. This means every seller that receives the information can extract more profit from the market without cutting down others' profits. Therefore, it is beneficial for the platform to share the individual information with more sellers.

We find that the sharing group size under optimal *AFS* tends to be smaller than the one under the optimal *AIS* with high $\frac{t}{\sigma}$, i.e. $K^*_{AFS} \leq K^*_{AIS}$. This is because, when $\frac{t}{\sigma}$ is high, the individual signal sent to each seller is less informative, whereas the full information set conveys much more information that is beneficial to sellers. In other words, sharing full information with a seller is more efficient in conveying market information. Therefore, fewer sellers should receive the full information in order to mitigate the correlation of sellers' quantity decisions.

Next, we show that when the number of sellers to share with (i.e., K^*_{AFS} and K^*_{AIS}) can be non-integer, the profit under *AFS* is always higher than that under *AIS*. However, if the number of sellers to share with has to be an integer (as is the case in practice), the optimal *AIS* strategy may outperform the optimal *AFS* strategy.

Lemma 2. *When K^* can take non-integer values, the optimal profit under different sharing formats has the following relationship: $\Pi^*_{AIS} \leq \Pi^*_{AFS}$. When K^* has to be an integer, then $\Pi^*_{AIS} > \Pi^*_{AFS}$ may occur under certain conditions.*

One may intuit that the platform should always prefer the *AFS* format to the *AIS* format because the latter is subject to the privacy constraint. However, interestingly, the above lemma indicates that the *AIS* format may yield a higher profit than the *AFS* format. That is, even though the privacy constraint forces the platform to only share individual information, the platform may benefit more from sharing individual information than sharing full information without privacy constraint. When $\min\left\{\frac{2}{b}-1, N\right\}$ is an integer, the optimal *AFS* is always better. When $\min\left\{\frac{2}{b}-1, N\right\}$ is not an integer, the platform has to compare the following four strategies and choose the one that yields the highest expected profit: (1) sharing full information with $\left\lceil \min\left\{\frac{2}{b}-1, N\right\}\right\rceil$ sellers, (2) sharing full information with $\left\lfloor \min\left\{\frac{2}{b}-1, N\right\}\right\rfloor$ sellers, (3) sharing individual information with $\left\lceil \min\left\{\frac{2(\sigma+t)}{b\sigma}-1, N\right\}\right\rceil$, and (4) sharing individual information with $\left\lfloor \min\left\{\frac{2(\sigma+t)}{b\sigma}-1, N\right\}\right\rfloor$ sellers. In this case, the optimal profit under the *AIS* format may be higher than that under the *AFS* format.

5. Information Sharing with Fairness Constraint

In this section, we consider the situation where the platform needs to satisfy the fairness constraint. In this case, the precision of information shared with every seller needs to be the same. Therefore, as discussed in Section 3, we also refer to these sharing formats as *Symmetric Full Sharing* and *Symmetric Individual Sharing* formats.

We first examine the *SFS* format. Under the *SFS* format, the platform combines demand signals from all sellers and shares the full information of the same precision with every seller. In other words, $y_i = \{\hat{x}_{1i}(m_{SFS,1i}), \ldots, \hat{x}_{Ni}(m_{SFS,Ni})\}$ and $m_{SFS,i_1j_1} = m_{SFS,i_2j_2}, \forall i_1, i_2, j_1, j_2$. The platform uses the precision matrix M_{SFS} to control the precision of the shared information. Proposition 4 characterizes the optimal *SFS* strategy for the platform.

Proposition 4 **(Optimal Symmetric Full Sharing)**. *The optimal SFS strategy is to provide full information with some noises to all sellers:* $y_i(M^*_{SFS}) = \{\hat{x}_{1i}(m^*_{SFS,1i}), \hat{x}_{2i}(m^*_{SFS,2i}), \ldots, \hat{x}_{Ni}(m^*_{SFS,Ni})\}$*, where the optimal level of noises is given by:*

$$m^*_{SFS,ij} = \max\left\{0, \frac{(b(N-1)-2)(N\sigma+t)}{2}\right\} \forall i, j. \tag{11}$$

The expected profit of the platform under this strategy is:

$$\Pi^*_{SFS} = \begin{cases} \frac{\alpha N a^2}{[2+b(N-1)]^2} + \frac{\alpha N \sigma^2}{(2+b(N-1))^2\left(\sigma+\frac{t}{N}\right)}, & \text{if } N \leq \frac{2}{b}+1, \\ \frac{\alpha N a^2}{[2+b(N-1)]} + \frac{\alpha N \sigma^2}{8b(N-1)(\sigma+\frac{t}{N})}, & \text{otherwise.} \end{cases} \tag{12}$$

Both the platform and the sellers can benefit from the optimal SFS strategy compared with the no-information-sharing benchmark case.

Equation (11) shows that the variance of noises added to the shared information is weakly increasing in the number of sellers N and the substitution level b. In other words, the platform should share less informative information in a more competitive market. In a market with a relatively small number of sellers and low substitution level, the competition between sellers is mild. In this case, $b(N-1) < 2$ and in turn $\max\left\{0, \frac{(b(N-1)-2)(N\sigma+t)}{2}\right\} = 0$, which implies that the optimal *SFS* strategy for the platform is to extract the value of the full information by truthfully sharing it with all sellers. However, as the market becomes more competitive with more sellers or higher substitution level, the platform will add independent noises to the full information before she shares the information with the sellers. The variance of the noises increases with the number of sellers and the substitution level to compensate for the loss resulting from the higher correlation of sellers' strategies caused by information sharing.

In a traditional Cournot competition setting with market uncertainty, the expected profit of a single seller decreases in the market size because more competition leads to lower profit for every seller. However, when information sharing by the platform is feasible and the platform adopts the optimal *SFS* strategy, each seller's profit may be increasing in the market size. In particular, we find that when the substitution level between sellers is low and the market size is small, having more competitors may increase each seller's expected profit. This result is formalized by Corollary 1.

Corollary 1. *When* $0 < b < \frac{\sigma^2 t}{(\sigma+t)[a^2(\sigma+t)+\sigma^2]}$, *and* $1 \leq N < -\frac{t[4a^2+\sigma]}{4\sigma[a^2+\sigma]} + \frac{1}{4[a^2+\sigma]}\sqrt{\frac{t}{b\sigma}\left[8\sigma(2-b)(a^2+\sigma)+bt(\sigma-8a^2)\right]}$, *each seller's profit increases in the number of sellers* N, *i.e.,* $\frac{\partial \pi_{i,SFS}(M^*_{SFS})}{\partial N} > 0$.

When the market size increases, it has two opposing effects on each seller. On one hand, the increase in market size will lead to more intense competition and thus lower profit for the sellers. On the other hand, the increase in market size will improve the precision of the shared full information, which leads to higher profit for all sellers. With a relatively small market size and a low substitution level, the profit loss from intensified competition due to market size expansion for each individual seller is outweighed by the benefits from obtaining more precise information. Therefore, as stated in Corollary 1, each seller may benefit from the increase of market size when the platform is allowed to share full information.

Next, we consider the *SIS* format where the platform only releases each seller's individual information to himself, and the information shared with different sellers needs to have the same precision. Proposition 5 characterizes the optimal *SIS* strategy.

PROPOSITION 5 **(Optimal Symmetric Individual Sharing)**. *The optimal SIS strategy is to provide the individual information with noises to each seller:* $y_i(M^*_{SIS}) = \{\hat{x}_{ii}(m^*_{SIS,ii})\}$*, where the optimal level of noises is given by:*

$$m^*_{SIS,ij} = \begin{cases} \max\left\{0, \frac{[b(N-1)-2]\sigma}{2} - t\right\}, & \text{if } i = j, \\ +\infty, & \text{otherwise.} \end{cases} \tag{13}$$

The expected profit of the platform under this strategy is:

$$\Pi^*_{SIS} = \begin{cases} \frac{\alpha N a^2}{[2+b(N-1)]^2} + \frac{\alpha N \sigma^2(\sigma+t)}{[(2+b(N-1))\sigma+2t]^2}, & \text{if } N \leq \frac{2(\sigma+t)}{b\sigma} + 1, \\ \frac{\alpha N a^2}{[2+b(N-1)]} + \frac{\alpha N \sigma}{8b(N-1)}, & \text{otherwise.} \end{cases} \tag{14}$$

Both the platform and the sellers can benefit from the optimal SIS strategy compared with the no-information-sharing benchmark case.

Similar to the optimal *SFS* strategy, the platform may not want to share the truthful demand signals with each seller as competition gets more intense. Equation (13) shows that the variance of added noises is weakly increasing in the substitution level b and the market size N, and is decreasing in the noise level of the original demand signals t. When the competition is mild, the

platform can fully utilize the individual signal by sharing it truthfully. When the market becomes more competitive (i.e., b or N gets larger), sharing information will correlate the strategies of different sellers more and result in greater losses. In this case, the platform needs to add more noises to attenuate such correlation between strategies caused by information sharing. Moreover, if the information from the original demand is limited (i.e., t is large), the sellers will correlate their strategies less after receiving the shared information, so the platform can add less noises to the shared information.

While each seller's profit can increase in the market size under the optimal *SFS* strategy, in the case of the optimal *SIS* strategy, each seller's profit can only decrease in the market size. The reason is that, under the optimal *SIS* strategy, each seller will not gain more precise information as the market size grows since each seller will only receive individual information. Therefore, the increase of market size can only negatively affect a seller's profit by intensifying the competition under the optimal *SIS* strategy.

Although both strategies satisfy the fairness constraint, the optimal *SFS* strategy violates the privacy constraint. We find that sharing individual information can be more profitable than sharing full information with large market size. In particular, Proposition 6 indicates that with a large number of sellers, the optimal *SIS* strategy, without violating the privacy constraint, dominates the optimal *SFS* strategy.

Proposition 6 **(Optimal Symmetric Sharing Format)**. *The optimal SIS strategy dominates the optimal SFS strategy when $N > \bar{N}(b)$, where*

$$\bar{N}(b) = \begin{cases} -\frac{t}{2\sigma} + \frac{\sqrt{4\sigma(\sigma+t)(2-b)^2+b^2t^2}}{2b\sigma} & \text{if } 0 < b < \frac{2t}{4\sigma+3t} \\ \kappa_2 & \text{otherwise,} \end{cases}$$

where κ_2 is the second root of

$$b^2\sigma^2\kappa^3 - 2b\sigma(2\sigma+2t+\sigma b)\kappa^2 + [\sigma^2(b+2)^2 + 4\sigma t(2-b) + 4t^2(1-2b)]\kappa + 8bt(\sigma+t) = 0.$$

The main intuition behind Proposition 6 relies on the trade-off between intensified competition and more precise information under both sharing strategies. The optimal *SIS* strategy provides each seller's individual information to himself, while the optimal *SFS* strategy provides each seller the information collected through all sellers' signals. Therefore, the increased correlation of strategies due to information sharing (i.e., the intensified competition) is more pronounced under the optimal *SFS* strategy compared to the optimal *SIS* strategy. When the market size is large and the competition among the sellers is intense, the increased correlation among the sellers' strategies will hurt each seller more. Therefore, when the market size is large, the optimal *SIS* strategy dominates the optimal *SFS* strategy.

6. Optimal Pricing Mechanism

In this section, we consider an extension where the platform can charge sellers for the information sharing service. We show that, by offering the same price menu to all sellers, the platform can achieve the optimal information sharing strategies without violating the fairness constraint. Such a pricing mechanism maximizes the platform's expected profit. Proposition 7 gives the optimal pricing mechanisms for both full information sharing and individual information sharing.

Proposition 7. *The platform can achieve the optimal AFS strategy and AIS strategy by offering the following pricing mechanisms:*

- *For AFS, the platform charges F^*_{AFS} for full information $\{x_1, x_2, \ldots, x_N\}$, where*

$$F^*_{AFS} = \frac{(1-\alpha)\sigma^2}{[2+b(K^*_{AFS}-1)]^2\left(\sigma+\frac{t}{N}\right)}. \tag{15}$$

Under this pricing mechanism, K^*_{AFS} sellers will choose to purchase the information in equilibrium, and the platform's expected profit is maximized under full information sharing.

- *For AIS, the platform charges F^*_{AIS} for individual information $\{x_i\}$ for seller i, where*

$$F^*_{AIS} = \frac{(1-\alpha)\sigma^2(\sigma+t)}{\left[(2+b(K^*_{AIS}-1))\,\sigma+2t\right]^2}. \tag{16}$$

Under this pricing mechanism, K^*_{AIS} sellers will choose to purchase the information in equilibrium, and the platform's expected profit is maximized under individual information sharing.

Proposition 7 states that, by setting the optimal price for the information sharing service as the profit gain for each seller in the sharing group under the optimal *AFS* (*AIS*) strategy, the platform can attract the exact same number of sellers to purchase the information as in the optimal asymmetric full (individual) sharing strategy. This is because the gain from acquiring the information for one seller in the equilibrium is strictly decreasing in the number of sellers who have already acquired the information. When the number of sellers who purchase the information sharing service is less than K^*_{AFS} (K^*_{AIS}), other sellers would still have incentives to purchase the information sharing service since the profit gain from information sharing exceeds the charged price (i.e., the information gain at K^*_{AFS} or K^*_{AIS}). However, when the number of sellers who purchase the information sharing service is greater than K^*_{AFS} (K^*_{AIS}), the profit gain from acquiring the information is lower than the price paid, and the sellers will stop purchasing the information. Therefore, only K^*_{AFS} (K^*_{AIS}) sellers will choose to use the information sharing service in equilibrium.

In the previous section, we have shown that the sellers will strictly benefit from information sharing in the equilibrium. Proposition 7 implies that the platform can maximize her own expected profit by taking the profit gain of every seller who purchases the information. Notice that even though not all the sellers will purchase the information in equilibrium, they are given the same price menu for the information. In this case, fairness is also achieved.

The optimal price for information depends on the market competition intensity and the precision of the information. Corollaries 2 and 3 characterize how the optimal price for information varies with these parameters.

Corollary 2. *For the AFS format, we find that: (i) The optimal price for full information, F^*_{AFS}, increases in the variance of the market uncertainty, σ, and decreases in the noise level of the signals observed by the platform, t. (ii) F^*_{AFS} decreases in the substitution level b when $0 < b \leq \frac{2}{N+1}$ and increases in b when $\frac{2}{N+1} < b \leq 1$. (iii) When $N \geq \frac{2}{b} - 1$, F^*_{AFS} increases in the number of sellers in the market, N. When $1 \leq N < \frac{2}{b} - 1$ and $\frac{t}{\sigma+t} < b \leq 1$, F^*_{AFS} decreases in N. When $1 \leq N < \frac{2}{b} - 1$ and $0 < b \leq \frac{t}{\sigma+t}$, F^*_{AFS} first increases and then decreases in N.*

The above comparative statics results are intuitive. When the market demand has higher uncertainty, i.e. greater σ, additional information would be more beneficial to the sellers. Therefore, the optimal price for the full information also increases. Moreover, the optimal price also depends on the precision of the signals provided by the platform. Since the platform never shares partial information with any sellers under the optimal AFS strategy, the precision of the information shared with sellers is the precision of the signals observed by the platform. When the observed signals are less accurate, i.e. t gets greater, the optimal price for the information will drop accordingly.

The optimal price F^*_{AFS} also relies on the substitution coefficient b. The optimal price varies non-monotonically in b because of the optimal sharing structure. Notice that when b is small ($0 < b \leq \frac{2}{N+1}$), the products sold by different sellers are highly differentiated, and the optimal sharing strategy is to share full information with all sellers. As b increases, the substitution level between products increases, which leads to higher level of competition. As a result, the profit gain due to information sharing for each seller decreases. However, as b further increases and exceeds $\frac{2}{N+1}$, the optimal AFS strategy is to share full information only with K^*_{AFS} sellers which decreases in b. Under the optimal pricing mechanism, the platform has to raise the price with greater b in order to lower the number of sellers who purchase the information sharing service in equilibrium.

The number of sellers in the market may also affect the optimal price. When the number of sellers exceeds $\frac{2}{b} - 1$, the number of sellers who purchase the information under the equilibrium remains unchanged. However, the precision of information gets higher with more sellers in the market, which leads to the price increase in N. When $N < \frac{2}{b} - 1$, every seller should be offered full information. On one hand, the increase of N leads to more accurate information. On the other hand, the competition level also increases. Therefore, the price may change non-monotonically in N.

Corollary 3. *For the AIS format, we find that: (i) The optimal price for full information F^*_{AIS} increases in the variance of the market uncertainty, σ, and decreases in the noise level of the signals observed by the platform, t. (ii) F^*_{AIS} decreases in the substitution level b when $0 < b \leq \frac{2(\sigma+t)}{(N+1)\sigma}$ and*

increases in b when $\frac{2(\sigma+t)}{(N+1)\sigma} < b \leq 1$. (iii) When $N \geq \frac{2(\sigma+t)}{b\sigma} - 1$, F^*_{AIS} stays unchanged as the number of sellers N changes. When $1 \leq N < \frac{2(\sigma+t)}{b\sigma} - 1$, F^*_{AIS} decreases in N.

For individual information sharing, the sellers never benefit from the increase of N due to the structure of the AIS format. Therefore, the optimal price would never increase in N.

7. Conclusion and Future Research

Motivated by the recent development of online retail platforms, this paper studies the optimal information sharing strategy from the perspective of a retail platform. First, we find that the platform has incentives to share information with the sellers, and such sharing is beneficial both to the platform and to all sellers. Second, we demonstrate that, when the sharing strategy can be asymmetric across sellers, the optimal sharing strategy is to select a subgroup of sellers and *truthfully* share (either full or individual) information with sellers in this subgroup. However, when the sharing strategy has to be symmetric across sellers, the platform has incentives to add noises to the shared information. Third, we propose a simple, single-price mechanism that can achieve the optimal information sharing outcome.

There are several promising directions to extend this study both theoretically and empirically. First, we focus on Cournot competition with substituitable products in this paper. It is worthwhile to study the optimal information sharing strategies under different types of competition models, especially Bertrand competition with substituitable products. Second, although we have considered sellers with heterogeneous market power as an extension, in practice, sellers may be heterogeneous in many other dimensions. From a practical perspective, it is important to extend our insights to an implementable information sharing algorithm based on high-dimensional characteristics of each seller. Finally, while our model is motivated by the practices at Alibaba and Amazon, its prediction also relies on our assumptions. Therefore, it would be interesting to study empirically how information sharing by Alibaba and Amazon affects the profit of the platform and the sellers in equilibrium.

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Appendix A: Extension—The Bertrand Model

Our main paper focuses on Cournot competition with strategic substitutes and uncertain linear demand. In this section, we show that our main results also hold for Bertrand competition when products are complementary. We consider Bertrand competition with complementary products since Raith (1996) shows that Bertrand competition with complementary products are similar to Cournot Competition with substitutable products. Consider the following demand function under Bertrand competition:

$$q_i = \zeta - p_i - \beta \sum_{d \neq i} p_d + \nu, \tag{17}$$

where $\zeta > 0$, $0 < \beta \leq 1$ and $\nu \sim N(0, \sigma)$. Similar to our Cournot model, this Bertrand competition describes a game with complementary products where sellers have downward-sloping reaction curves. Focusing on the same sharing formats as in our main paper, we show that the result in Proposition 1 still holds in this Bertrand competition:

Corollary 4 **(Optimal Sharing Format in the Bertrand model)**. *Consider the above Bertrand model with complementary products. Under the optimal AFS and AIS sharing strategy, the platform will never partially share any information with any sellers (i.e., $m^*_{ij} \in \{0, +\infty\}$, $\forall m^*_{ij} \in M^*_{AFS}$ or M^*_{AIS}).*

As shown in Raith (1996), the information sharing equilibria heavily depend on the type of competition, the source of uncertainty, and the product characteristics. Our main model is a Cournot model with linear demand, strategic substitutes, and common demand uncertainty. Corollary 4 shows that we can draw similar conclusions for Bertrand markets with strategic complements, caeteris paribus. However, this does not guarantee that the same insights will carry over to settings where the Bertrand model is nonlinear or has cost uncertainty instead of demand uncertainty. Raith (1996) provides more discussion on how different information structures may change the information sharing equilibria.

Appendix B: Extension—Heterogeneous Sellers

For clarity of analysis and ease of exposition, the sellers are assumed to be homogeneous in the main model. Here we extend the base model to check robustness of results and derive additional insights. Specifically, we consider a case where the sellers are heterogeneous in their market power. There are two types of sellers in the market: high-type sellers with high market power and low-type sellers with low market power. A high-type seller's quantity decision has a greater impact on the other sellers' prices, whereas a low-type

seller has a relative small impact on the other sellers. Among the N sellers, suppose there are N_H and $N_L = N - N_H$ sellers of each type. We further define $H = \{1, \ldots, N_H\}$ and $L = \{N_H + 1, \ldots, N_H + N_L\}$. These sellers participate in Cournot competition. The inverse demand function can be written as:

$$p_i = \begin{cases} a - q_i - b_H \sum_{k \in H, k \neq i} q_k - b_L \sum_{k \in L} q_k + u, & \text{if } i \in H \\ a - q_i - b_H \sum_{k \in H} q_k - b_L \sum_{k \neq j, k \in L} q_k + u, & \text{if } i \in L. \end{cases}$$

With $b_H > b_L$, we can see that for high-type sellers, their quantity decisions will have greater influences on other sellers' prices, whereas the quantity decision of a low-type seller will have smaller influences. When the platform does not share any information with both types of sellers, we can show that the high-type sellers will have higher equilibrium profits. Therefore, we can characterize the sellers' market powers based on their equilibrium profits.

We first focus on the case when sharing formats can be asymmetric, and demonstrate that the following three structural results of optimal asymmetric sharing strategies remain true when sellers become heterogeneous. First, we show that when the sellers have heterogeneous market power, the platform is still willing to share information, and information sharing is beneficial to both the sellers and the platform. Second, we prove that the platform still has no incentive to partially share information with any sellers under the optimal *AFS* and *AIS* strategies even when sellers are heterogeneous. Third, we show that optimally sharing individual information (i.e., the optimal *AIS* strategy) can sometimes generate more profit for the platform compared to optimally sharing full information (i.e., the optimal *AFS* strategy). The following corollary summarizes these results about optimal asymmetric sharing strategies.

Corollary 5 **(Optimal Asymmetric Sharing with Heterogeneous Sellers)**. *When the sellers are heterogeneous in market power, we find that: (a) both the platform and the sellers can be weakly better-off with information sharing under both AFS and AIS formats; (b) the platform will never partially share any information with any sellers under the optimal AFS and AIS strategies (i.e.,* $m^*_{ij} \in \{0, +\infty\}$, $\forall m^*_{ij} \in M^*_{AFS}$ *or* M^*_{AIS}*); (c) when* K^*_H *and* K^*_L *have to be integers, the optimal AIS strategy may dominate the optimal AFS strategy under certain conditions.*

We then focus on the symmetric sharing formats, and show that the structural properties of the optimal symmetric sharing strategies remain the same under these formats when sellers become heterogeneous. The following corollary summarizes these two structural results about the optimal symmetric sharing strategies.

Corollary 6 **(Optimal Symmetric Sharing with Heterogeneous Sellers)**. *When the sellers are heterogeneous in market power, we find that: (a) both the platform and the sellers can be better-off with information sharing under both SFS and SIS formats; (b) the optimal SIS strategy may dominate the optimal SFS strategy under certain conditions.*

Next, we study the exact optimal sharing strategies when the sellers are heterogeneous, rather than their structural properties. We cannot characterize the closed-form representation of the optimal symmetric sharing strategies. However, we are able to characterize the closed-form optimal asymmetric sharing strategies when the sellers are heterogeneous, and this result may be more interesting given that the platform has more incentives to employ asymmetric sharing strategy when sellers are heterogeneous. In particular, the platform would prefer to offer information to sellers that have relatively low impact on the others to ensure that other sellers' gain on expected profit by receiving the information outweighs the decrease due to higher correlation of strategies. Proposition 8 formalizes such intuition.

Proposition 8 **(Optimal Asymmetric Sharing Strategies with Heterogeneous Sellers)**. *When the sellers are heterogeneous in market power: under the optimal AFS strategy, the platform shares full information truthfully with K_H^* high-type sellers and K_L^* low-type sellers, respectively.*

- *If $N_L \geq K_{L,AFS}^* = \frac{2}{b_L} - 1$, $K_L^* = K_{L,AFS}^*$ and $K_H^* = 0$;*
- *If $\bar{N}_{L,AFS} \leq N_L \leq K_{L,AFS}^*$, $K_L^* = N_L$ and $K_H^* = 0$;*
- *If $0 \leq N_L < \bar{N}_{L,AFS}$, $K_L^* = N_L$ and $K_H^* = \min\{\bar{K}_{H,AFS}(N_L), N_H\}$.*

The expressions of $\bar{N}_{L,AFS}$ and $\bar{K}_{H,AFS}(\cdot)$ are given in the proof in the online appendix.

When sellers are heterogeneous in market power, under the optimal AIS strategy, the platform shares individual information truthfully with K_H^* high-type sellers and K_L^* low-type sellers, respectively.

- *If $N_L \geq K_{L,AIS}^* = \frac{2(\sigma+t)}{b_L \sigma} - 1$, $K_L^* = K_{L,AIS}^*$ and $K_H^* = 0$;*
- *If $\bar{N}_{L,AIS} \leq N_L \leq K_{L,AIS}^*$, $K_L^* = N_L$ and $K_H^* = 0$;*
- *If $0 \leq N_L < \bar{N}_{L,AIS}$, $K_L^* = N_L$ and $K_H^* = \min\{\bar{K}_{H,AIS}(N_L), N_H\}$.*

The expressions of $\bar{N}_{L,AIS}$ and $\bar{K}_{H,AIS}(\cdot)$ are given in the proof in the online appendix.

The optimal sharing strategy depends on how many sellers there are for each type. When the number of low-type sellers is large, the platform only shares the demand information truthfully with these low-type sellers. In this case, the optimal sharing group size is the same as if all sellers in this market are of low

type. They are all relatively small sellers whose actions do not have significant impacts on others. However, when the low-type group size is relatively small, the platform may want to release the demand information to the high-type sellers as well. In fact, when the platform has several low-type sellers but not too many, the platform may still not share any information with the high-type sellers. This happens when the number of low-type sellers is slightly smaller than the optimal sharing group size for the low-type sellers under asymmetric information sharing format, $K^*_{L,AFS}$ or $K^*_{L,AIS}$. The effect of intensified competition brought by including high-type sellers in the information sharing group exceeds the profit increase from fully utilizing information. Furthermore, when the platform only has very few low-type sellers, the platform will provide the demand information to the high-type sellers anyway. The number of high-type sellers that receive the information depends on the number of low-type sellers. Intuitively, with more low-type sellers in the market, the fewer high-type sellers will be offered the information.

Appendix C: Extension—Sellers with Private Information

In this section, we study an extension of our main model where each seller can observe a private signal in addition to the prior distribution of the demand uncertainty. For instance, each seller can at least get his own sales data. Therefore, each seller can get a noisy signal about the demand uncertainty based on these sales information even without anything from the platform. Suppose seller i observes the demand signal x_i^{sales} given by

$$x_i^{sales} = u + \nu_i,$$

$$\nu_i \sim N(0, s_i),$$

$$cov(\nu_i, e_j) = 0, \forall i, j.$$

When the platform does not provide any information to the sellers, they will update their beliefs based on their own private signals and then make the quantity decisions. On highly digitized retail platforms, the information obtained by the sellers is often a subset of the information collected by the platform. Therefore, we assume, without loss of generality, each seller's individual signal is known to himself and the platform, but not to his competitors. The platform knows the sellers' private signals $\{x_i^{sales}\}_{i=1}^N$ and also observes $\{x_i\}_{i=1}^N$ based on the superior information.

The platform can decide how to share $\{x_i\}_{i=1}^N$ with the sellers by controlling the precision matrix M. The noises added to the signals are random and $cov(\epsilon_{ij}, \nu_k) = 0, \forall i, j, k$. Seller i receiving $y_i =$

$\{\hat{x}_{1i}(m_{1i}), \hat{x}_{2i}(m_{2i}), \ldots, \hat{x}_{Ni}(m_{Ni})\}$ would combine the information y_i from the platform with his private information x_i^{sales} to form his belief about the market. We find that the structure of the optimal information sharing format remains unchanged with such private information. The platform has no incentive to share partial information with any sellers.

COROLLARY 7 **(Optimal Sharing Format with Private Information)**. *When the sellers can observe private signals, the platform will never partially share any information with any sellers under the optimal AFS and AIS formats (i.e.,* $m_{ij}^* \in \{0, +\infty\}$, $\forall m_{ij}^* \in M_{AFS}^*$ *or* M_{AIS}^**).*

Corollary 7 further validates our finding that limiting the number of sellers to share information with is more efficient than adding noises to each seller's information even when the sellers can observe their own private signals.

Appendix D: Extension—An Auxiliary Model

In this section, we investigate an auxiliary model where each seller i observes his individual information x_i, and the platform observes the information from all sellers, i.e., $\{x_1, x_2, ..., x_n\}$. This new information structure creates a key difference from our main model: In this new model, platform does not own superior information compared to the sellers.

We are interested in this new information structure since it lies between the information structures in our main model and the traditional information sharing models (Gal-Or 1985, Raith 1996). This new model will help us understand the driving forces behind the fact that our results are different from the existing literature. Similar to the traditional information sharing models, the platform in this new model does not own superior information than the sellers; and the only difference between this new model and traditional information sharing models is that platform exists and serves as a central information sharing decision-maker.

We highlight two main differences between our Proposition 1 and the results in the existing literature. First, we show that the platform is willing to share information, which is different from the results in (Gal-Or 1985) that the sellers do not share information in equilibrium. Second, we show that the platform prefers sharing information truthfully with a subset of sellers to sharing noisy information with all sellers. Corollary 7 shows that in this new model where the platform does not have superior information, it may still choose to share information with the sellers. This indicates that the difference between our result and those in the literature is driven by the decision role of the platform, not by the superior information owned by the

platform. In other words, it reveals the informational role of the platform that facilitates information sharing to benefit all parties in this problem setting.

COROLLARY 8. *Consider a situation where each seller i observes his own individual information $\{x_i\}$, and the platform owns $\{x_1, \ldots, x_N\}$. The platform may still choose to share information with the sellers under certain conditions.*

In addition, we study whether the platform will truthfully share information with the seller as in Proposition 1. We focus on two types of information sharing formats: 1) sharing full information truthfully with a subset of sellers (i.e. K sellers), and 2) symmetrically sharing full information with some noise to all sellers. Corollary 9 below shows that sharing information with a limited number of sellers tends to be more profitable for the platform than symmetrically sharing less precise information with all sellers, which is consistent with Proposition 1.

COROLLARY 9. *Consider a situation where each seller i observes his own individual information $\{x_i\}$, and the platform owns $\{x_1, \ldots, x_N\}$. The optimal symmetric full sharing strategy is less profitable for the platform than sharing full information truthfully with the optimal number of the sellers with group size K^* when K^* can can be treated as a continuous number between 0 and N.*

In Corollary 8, we allow the optimal number of sellers to truthfully share information to be a continuous number; however, in practice, the optimal number needs to be an integer between 1 and N. Therefore, the claim in Corollary 9 is weaker than that in Proposition 1. Nevertheless, the main message remains consistent with Proposition 1. That is, controlling the sharing group size tends to be more efficient that controlling the accuracy of information in information sharing.

To provide additional robustness check, we explore the asymmetric full information sharing format with either two sellers or three sellers. We are able to prove that Proposition 1 holds for these two cases. The result is presented in Corollary 10.

COROLLARY 10. *Consider a situation where each seller i observes his own individual information $\{x_i\}$, the platform owns $\{x_1, \ldots, x_N\}$, and $N \leq 3$. The platform would never partially reveal full information with any sellers in the optimal asymmetrical full sharing strategy.*

Appendix E: Information Sharing Examples from Business Advisor

We provides examples of information that is provided to sellers by Business Advisor at Alibaba. Some information in the picture is blocked or blurred due to confidentiality reasons.

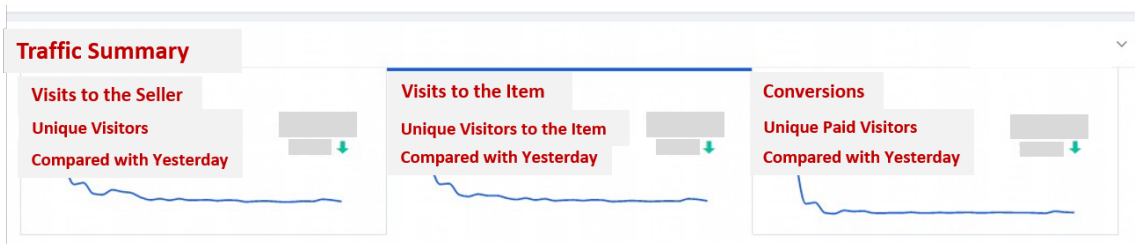

Figure 1 **Traffic Information. Sellers can see their traffic information summary through Business Advisor such as unique visits to the seller, unique visits to each item and the unique buyers, and how these indexes change over time.**

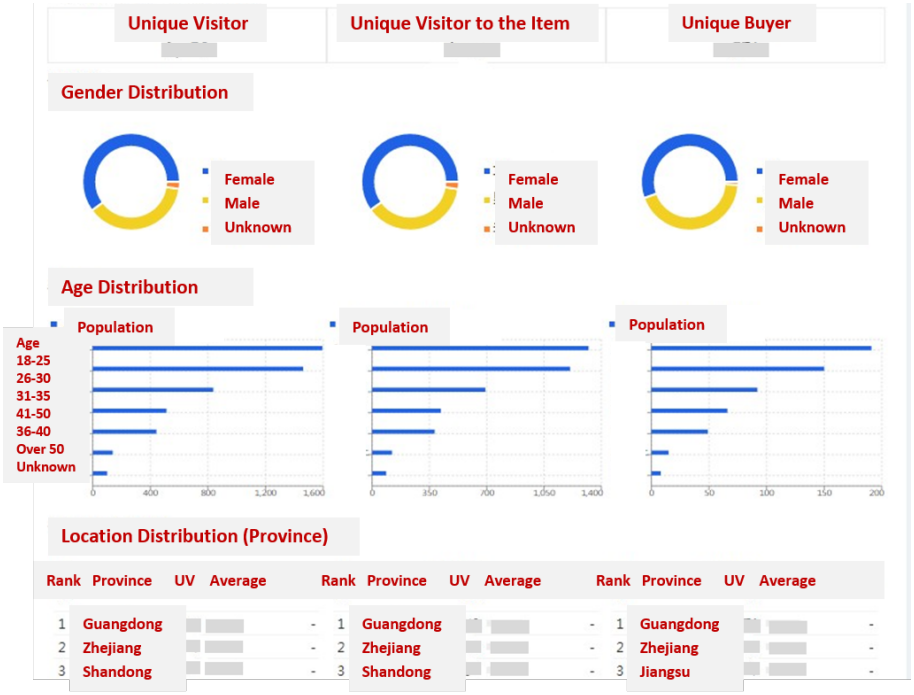

Figure 2 **Traffic Information with Customer Portrait. Business Advisor also provides detailed information about each seller's potential customers including the gender, age, and location distributions of the visitors.**

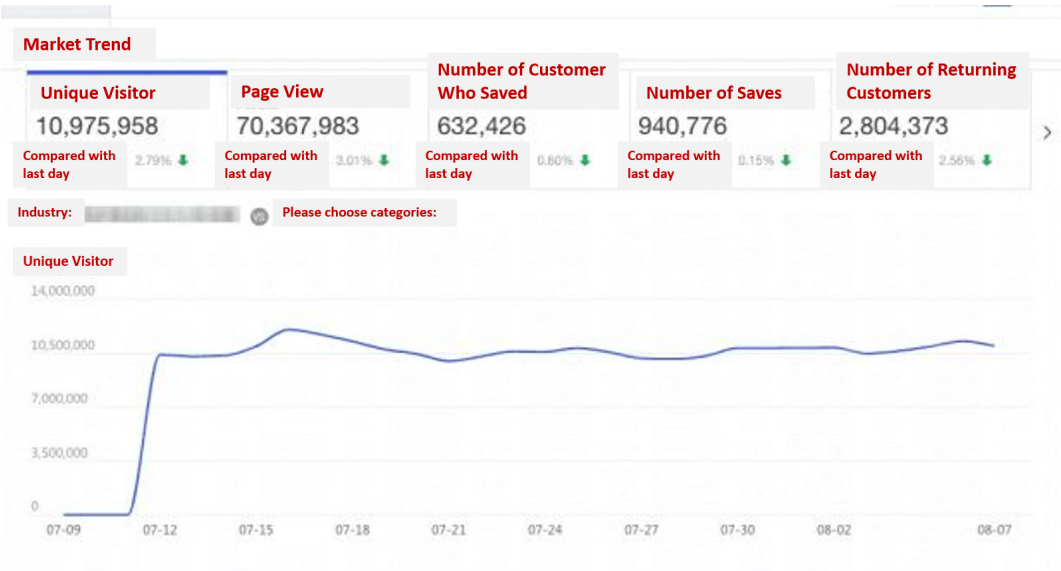

Figure 3 **Market Trend Information. Business Advisor provides aggregate information for all sellers in the same market, such as unique visitor and page views, and how these indexes change over time.**

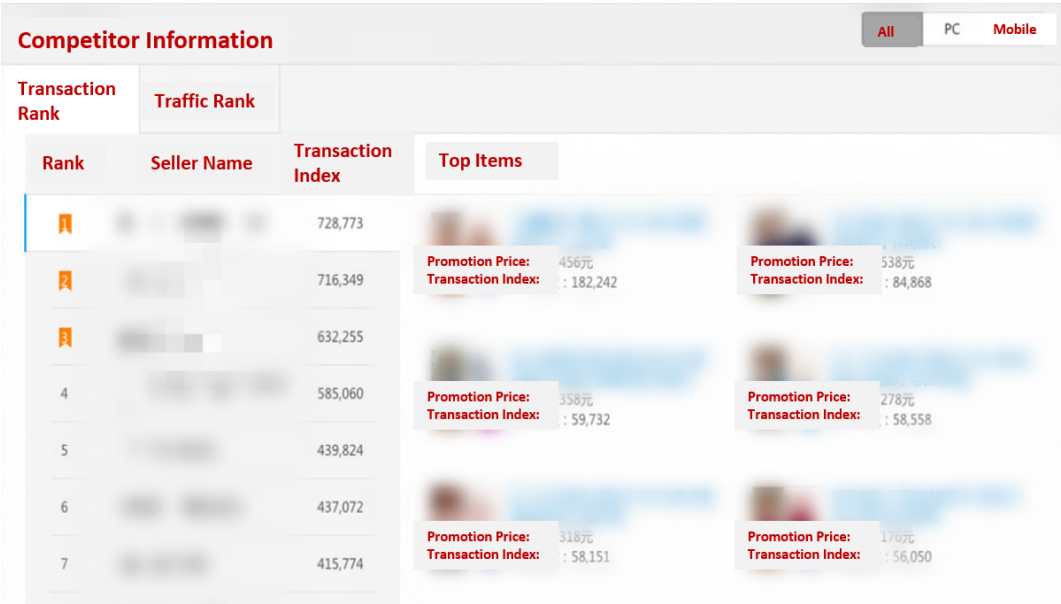

Figure 4 **Competitors' Information. The competitors' information in the same market such as traffic and transaction information is also available other than the aggregated market information.**