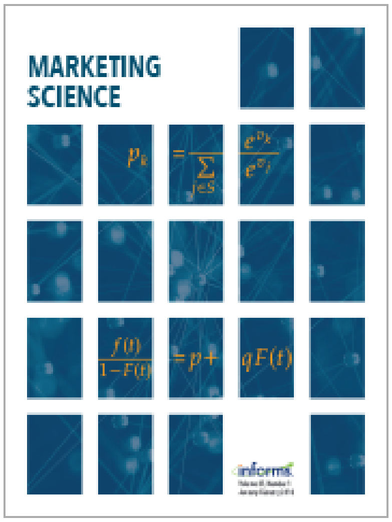

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Designing an Online Retail Marketplace: Leveraging Information from Sponsored Advertising

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Abstract. E-commerce platforms, such as Amazon and Alibaba, enable hundreds of millions of consumers to search and purchase products offered by millions of independent sellers who can advertise their products on the platforms. In this paper, we study how to design such a marketplace when there are two types of asymmetric information—sellers have some private information about their products that the platform does not have, whereas the platform has private information about consumers that the sellers do not have. Using a game theory model, we formulate the marketplace design problem as maximizing marketplace profit (comprising ad revenues and sales commissions) by jointly considering the following elements: ensuring sellers join the platform, specifying the auction that enables sellers to advertise in the sponsored list, leveraging the information revealed in the ad auction to refine the organic list, and setting the commission rate on sales to consumers who are rational and heterogeneous in their preferences. We show that sellers' bids in ad auctions, through which sponsored slots are allocated, can reveal the sellers' private information to the platform ("information effect"), which it can optimally combine with information that it has about consumers to improve the placement of organic results, a practice we call "strategic listing." However, by introducing an externality between the sponsored and organic sides, strategic listing also leads to more competition in the ad auction ("competition effect"), thus reducing the incentive of sellers to join the platform. The platform can incentivize sellers to join by reducing the commission rate on sales; however, under certain conditions, the platform must also reduce the degree of strategic listing (i.e., commit to limiting the influence of the sponsored ad auction outcomes on the placement of organic results). If the sellers' participation is sufficiently difficult to induce, the platform obtains a larger proportion (under some conditions, all) of its revenue from advertising than from sales commissions. Our results shed light on the variation in practices across different platforms and provide timely guidance for platforms to refine their marketplace design.

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1. Introduction

In the past decade, there has been explosive growth of e-commerce marketplaces, where millions of third-party sellers sell directly to hundreds of millions of consumers, with the platform providing the enabling marketplace infrastructure.[1] In the United States, Amazon accounts for 49% of online retail sales, and, based on recent data, more than two million third-party sellers are selling on Amazon, accounting for more than half of the units sold (Lunden 2018). In China, Alibaba constitutes 51% of the e-commerce market share, and it relies exclusively on third-party sellers (of which there are around 10 million).[2] In India, both Amazon and Flipkart, which together constitute nearly two-thirds of the e-commerce market, also operate through a marketplace model (Koetsier 2018).

An e-commerce marketplace is an ecosystem with complex interactions between consumers, sellers, and the platform. Consumers, who are heterogeneous in their preferences, search for products, with a consumer typically starting her search through a query. As consumers search, the platform lists third-party sellers' products in organic listing slots based on its best estimation of what consumers will like (using massive amounts of data and high-powered algorithms), whereas sellers can pay to advertise their products in sponsored listing slots. Furthermore, sellers have some degree of private information about their products that the platform does not have, whereas the platform has private information on consumers' preferences, gathered through historical consumer data, that the sellers do not have—both of these types of information are useful in determining the best matching products for consumers. In this setting, we study how the platform should set key design parameters of first-order importance to maximize its profit, which comprises sales commissions and ad revenues from auctions for sponsored slots. The platform needs to ensure that sellers join the platform and that their products are displayed to consumers in the organic and sponsored slots. In doing this, the platform balances the demand from consumers, which leads to revenues from sales commissions and the revenue from sponsored advertising.

In recent years, there has been an explosive growth of sponsored advertising on e-commerce platforms. In fact, the growing relevance of e-commerce platforms for product search is causing marketers to rethink their paid search campaigns and is posing a real challenge to search engines, which have long dominated search advertising budgets. In the United States, Amazon is building its own digital advertising business, the revenue from which has been estimated to be over \$14 billion in 2019 (Marvin 2020), and is expected to grow at a sharper rate in the future relative to other revenue sources (e.g., sales commissions from third-party sellers). Walmart is revamping its digital advertising business to generate increased revenue (Patel and Bruell 2021). Alibaba and Flipkart, which are the dominant online marketplaces in China and India, respectively, also earn significant fractions of revenue from third-party sellers' ads.

Although sponsored advertising is becoming a significant revenue driver for e-commerce platforms, we argue that its role in the marketplace is beyond just an additional revenue stream—in fact, it can play an important *informational* role. To see how, note that a major challenge for e-commerce marketplaces when ranking products optimally in response to a query is the private information about their products that third-party sellers possess. Consider a third-party seller who introduces a new design element, that is not observable by the platform, into her product to improve its quality and durability; for instance, a suitcase seller might introduce a sturdier zipper. The platform may be able to learn about such an attribute through consumer reviews, but this learning will take time, and by then, a new improvement may be introduced that the platform may again not be able to observe. Recent empirical papers (e.g., Abhishek et al. 2020) have documented the existence of such information asymmetry between the marketplace and its third-party sellers (Sahni and Zhang (2020) find the same type of information asymmetry in the context of search engines). In conversations with us, managers and researchers at several leading platforms (e.g., Amazon, Alibaba, Zomato, and Flipkart) have expressed, in no uncertain terms, that this is indeed a significant problem that they face.

However, as mentioned earlier, platforms typically sell sponsored ads through auctions in which third-party sellers bid. Interestingly, the sellers' bids in the ad auctions may reveal, at least to some degree, the private information that they hold about the products that they carry. Thus, the platform can learn this information from the bids and use this information to improve the ranking of organic listings. In other words, the platform can use this information to improve the set of results shown to the consumers and influence demand. This externality between the sponsored and organic sides implies that sellers will change their bidding behavior in the ad actions as well. Therefore, the platform will need to carefully decide how and to what degree it should use the information it learns, and how it should concomitantly change other parameters such as the sales commission rate. Clearly, the informational role of sponsored ads becomes an important element in marketplace design. For instance, according to industry observations, the search advertising revenue from Apple's app store is "a drop in the bucket" relative to the informational value it brings to the ecosystem because "by allowing app developers to signal their own value by bidding on keywords, consumers will end up finding apps that are better for them" (Gans 2016).

In this paper, we study the problem of optimal marketplace design when the sellers and the platform have private information (on products and consumers, respectively) and consumers are heterogeneous in their preferences and are rational. We ask the following broad questions: To what degree should the platform use the information it learns about products from the sponsored ad auctions to influence the organic results? Concomitantly, how should the platform adjust other parameters, for example, the sales commission rate that it charges to third-party sellers? How will such a strategy by the platform affect its advertising revenue, sales revenue, and overall revenue? What will be the impact on sellers' bidding behaviors in the sponsored ad auctions, on their participation at the platform, and on their profits? Last but not least, what will be the impact on the consumers in terms of demand?

To answer these questions, we develop a rich model of an online marketplace. We assume that both sellers and the platform have some private information about different components of the match probability between sellers' products and consumers (specifically, about product attributes and consumer preferences, respectively). The platform runs a second-price auction to allocate a sponsored ad slot, which is followed by an organic slot. The platform may engage in the practice of "strategic listing," that is, it may leverage information obtained from bids in the ad auction to improve the allocation of its organic listing. Consumers are rational—they update their beliefs about match probabilities with different products and search strategically based on the sponsored and organic placements chosen by the platform. For each product sold, the platform charges a commission as a percentage of the transaction revenue. Thus the platform has revenue from both advertising and sales. To maximize its total revenue, the platform must choose an "information weight" or "information sharing" parameter to determine the dependence of organic ranking on the information learned from sellers' bids, which it can encode in its search response algorithm. Concomitantly, the platform chooses the commission rate to ensure that sellers facing an outside option participate in selling on the platform.

We find that exploiting information from ad auctions helps the platform to infer sellers' private information and improve the ordering of organic results; we call this the "information effect" of strategic listing. From a sales revenue perspective, the platform uses the information it learns from sellers and the information it already has in a balanced manner to maximize product sales. From an advertising revenue perspective, strategic listing influences advertising competition between sellers. This is because under strategic listing, there is an externality—the bids influence not only the placement in the sponsored slot, but also influence the placement in the organic results. In particular, strategic listing can intensify advertising competition by making the winner of the ad auction more likely to get a better placement in the organic listing as well; we call this the "competition effect" of strategic listing. Although this improves the platform's advertising revenue, it disincentivizes sellers to participate in selling on the platform in the first place.

To incentivize sellers' participation, the platform can reduce the sales commission rate or the information weight (or both). Importantly, reducing the commission rate merely transfers surplus from the platform to sellers; on the other hand, reducing the information weight not only transfers surplus to sellers (competition effect) but also reduces the total surplus that can be transferred because it worsens the quality of the organic placement and therefore reduces the demand (information effect). Therefore, the platform prioritizes reducing the commission rate over reducing the information weight. In fact, as the sellers' outside option increases and their participation becomes more difficult to induce, the platform may decrease the commission rate to zero and rely solely on advertising for profits.

We also obtain insights for the impact of strategic listing on all players by comparing the focal strategic listing scenario to an "independent listing" scenario in which sponsored and organic rankings are determined independently. We find that the platform obtains less commission revenue but more advertising revenue under strategic listing than under independent listing. Overall, strategic listing benefits the platform in the whole parameter space. Consumer demand is higher, that is, consumers are able to find better matching products, because the organic listing is now executed with better information. Also, sellers join the platform for a wider set of conditions under strategic listing, and they bid more aggressively in the ad auction.

Our results shed light on the variation in practices across different platforms and provide timely guidance for platforms to refine their marketplace design. We find that platforms can benefit from using information from ad outcomes to influence organic results. There is some indication that such strategies are employed in the industry; for instance, marketing agencies report that a higher ranking in the sponsored list on Amazon correlates with more visibility in the organic list.[3]

We also present an explanation for why different platforms may have different proportions of sales commission revenue and advertising revenue; specifically, as it becomes more challenging to incentivize sellers' participation, the platform should charge a lower commission rate and rely more on advertising revenue. Our result aligns with recent developments in the e-commerce industry in the United States. For instance, for Black Friday through Cyber Monday season in 2020, sales from small vendors using Shopify ($5.1 billion; Evans 2020) surpassed sales from Amazon's third-party sellers ($4.8 billion; Shead and Palmer 2020). This shows that small third-party sellers now have viable options beyond Amazon. As sellers' outside options improve, we observe that Amazon increasingly relies on advertising as a source of revenue. Indeed, advertising's coverage on an Amazon page, compared with recommendations and personalized content, has been steadily increasing (Kaziukėnas 2021).

Related to this, note that Alibaba, a Chinese platform with approximately ten million third-party sellers, relies primarily on advertising revenue while charging a minimal commission rate for each transaction (< 5%). On the other hand, Amazon, which has approximately two million third-party sellers, charges a significantly higher commission rate (between 10% and 25%, depending on the category) and depends on ad revenue to a lesser extent. Our theory suggests that this may be due to the relative attractiveness of the outside option on these platforms. Although one has to be careful in making comparisons, as Alibaba and Amazon operate in quite different market settings, nevertheless, one could argue that a much larger number of third-party sellers on Alibaba compared with Amazon makes Alibaba a more competitive marketplace, which makes outside options relatively more attractive, thus leading to lower commission rates, as per our theory.

Our focus is on e-commerce marketplaces, which are quite different from regular search engines such as Google and Bing. At e-commerce marketplaces, both organic and sponsored listings are meant for product sales; therefore, the information revealed from a sponsored listing can directly contribute to organic rankings. On the other hand, the nature of organic and sponsored listings in the context of a pure search engine can be very different—an organic listing is typically information oriented, whereas a sponsored listing is more product oriented. Furthermore, to make sure that search advertising does not affect the reputation of their core internet search products, search engines such as Google explicitly promise that the listings that appear in search advertising do not affect the rankings or listings of the regular organic search results. Nevertheless, some of our results shed light on the practices of search engines. First, search engines derive value from long-term user engagement through the quality of organic results, which implies that their "commission rate" can be assumed to be exogenous. We find that, in such a setting, it can indeed be optimal for the search engines to commit to independent listing. Second, recently, search engines have tried to regain lost ground from retail platforms by monetizing consumers' e-commerce activities. Google, for example, introduced the Shopping Actions program, which enables retailers to list products in response to search queries at Google, and it charges a commission fee for each sale from the Google Shopping listings.[4] Our key results are applicable in such a setting. Therefore, amid the trend of traditional search engines and retailing platforms encroaching on each other's territory, our framework provides timely guidance to the platforms to refine their design elements.

The rest of this paper is organized as follows. In Section 2, we discuss related literature. In Section 3, we formally describe the model. In Section 4, we analyze the implications of strategic listing on consumers' search strategies and sellers' bidding strategies, and investigate the platform's optimal marketplace design decisions. In Section 5, we present extensions to the model that help to obtain additional insights beyond those from the main model. In Section 6, we conclude with a discussion.

2. Relevant Literature

Broadly, our paper is related to two streams of literature: the literature on platforms and the literature on sponsored search advertising. We combine these two streams of literature by studying the interaction between the platform's advertising revenue and sales commissions in the presence of asymmetric information at e-commerce marketplaces.

A growing literature has focused on the economics of e-commerce platforms, especially on the matching between sellers and consumers. In particular, the informative role of advertising in e-commerce platforms facing asymmetric information has been supported by some recent empirical papers. For example, Abhishek et al. (2020) employ a field experiment at the leading Indian online marketplace Flipkart to show that independent sellers have relevant private information and that sponsored ads can work as a screening mechanism to identify high-relevance products. Sahni and Zhang (2020) show that sponsored ads at search engines can, under some conditions, provide better matching results than organic results. Sahni and Nair (2020) conduct a field experiment on the online food delivery and restaurant search marketplace Zomato to show that advertising can serve as a signal that leads to enhanced evaluations of advertised restaurants. Jiang et al. (2011) also study the asymmetric information problem between a platform owner and third-party sellers and show that third-party sellers may have the incentive to "countersignal"; that is, high-quality sellers may want to pose as low-quality sellers. Our work adds to these studies by further examining how product quality information revealed from sellers' bids can help a platform to improve its organic listings and how this influences the design of other aspects of the platform, such as the choice of the commission rate. We note that sellers in our model do not use their bids to "signal" their types to the platform; instead, we use a mechanism design approach in which the seller types are revealed in equilibrium.

We derive implications of how the platform should balance revenue from commissions on sales versus revenue from advertising fees, a question that is related to the literature on platform monetization. Choi and Mela (2019) study the monetization of online marketplaces by optimally trading off sponsored and organic results; however, they do not consider the transfer of information from the sponsored side to the organic side. Abhishek et al. (2016) also study contracting structures at online marketplaces to balance different sources of revenue. Ke et al. (2020) compare the platform's revenue when it relies solely on sponsored advertising versus when it relies solely on personalized organic listings; different from their paper, our focus is on how the platform balances revenues from both sides. Zhong (2020) considers the platform design problem in choosing the optimal search precision, when sellers set price strategically in response to the precision of search targeting. None of these papers, however, consider the platform's revenue streams from both advertising and commissions, and the information spillover from advertising to the organic side.

Several other related papers consider the platform design problem with a focus on how an informed intermediary may direct consumer search for its own benefit. Armstrong and Zhou (2011) consider an intermediary's incentive to bias its recommendations in favor of firms from which it receives larger payments. Hagiu and Jullien (2011) analyze the incentive for an intermediary who has superior information about the match between consumers and stores to direct consumers to their least favorite store to increase consumer traffic thus earning more per-visit fees. On a similar note, Eliaz and Spiegler (2011) discuss an intermediary's incentive to include more firms with low relevance to generate more clicks. Cornière and Taylor (2014) study the bias of a search engine that competes with publishers to attract advertisers and find that the search engine is biased against publishers that display many ads. Teh and Wright (2020) study an intermediary's trade-off between steering consumers toward a seller who pays more commissions per conversion, versus a lower-priced seller who has a higher conversion rate. We contribute to this stream of literature by studying not only how an intermediary directs consumer search via its organic listing, but also the effect on sellers' participation in selling on the platform.

Sponsored search advertising, mechanisms for position auctions and their equilibrium properties have been investigated extensively (Edelman et al. 2007; Varian 2007; Athey and Ellison 2011; Chen and He 2011; Jerath et al. 2011; Zhu and Wilbur 2011; Gomes and Sweeney 2014; Sayedi et al. 2014, 2018). Among these, Chen and He (2011) and Jerath et al. (2011) study the bidding strategies of vertically differentiated firms and the informative role of paid placement to reveal sellers' private information about the relevance of their products, improving efficiency of consumer search. Although our work has this as an operative force, it departs from this stream of literature by focusing on how the ad auction interacts with the organic listing. The possible ways of how search ads can interact with organic listings have been studied by Katona and Sarvary (2010), Berman and Katona (2013), Yang and Ghose (2010), White (2013), and Agarwal et al. (2015). Specifically, Berman and Katona (2013) jointly study search engine optimization and sponsored search advertising and find that high-quality websites invest in search engine optimization, whereas low-quality websites focus on winning the ad auction. Unlike Berman and Katona (2013), in our model, the platform also earns organic revenue, and our focus is the interaction between the platform's advertising revenue and sales commissions from organic listing. Our work contributes to this stream of literature by studying such an interaction from the perspective of information spillovers in the presence of asymmetric information.

3. Model

We assume that there are two sellers who sell their products on a marketplace. Consumers visit the marketplace and each consumer enters a search query to receive a list of products arranged in a ladder with both sponsored and organic listings.[5] Sellers can pay to be placed in the sponsored list, whereas the platform determines the placement of products in the organic list. Consumers search through the ladder of results, and if a consumer purchases a product, the platform charges the seller a commission fee. We now describe the various components of the model in detail.

3.1. Information Structure

We employ a Bayesian game framework in which both the seller of a product and the platform have some private information regarding different components of the preference of the consumers for the product.[6] This preference is determined by both vertical and horizontal aspects.

First, consider the vertical aspects of a product. These can be of two types: those that can be observed or learned by the platform through its data collection and processing, and those that cannot be learned by the platform but are known to the seller. Our focus in the model is on the latter type of vertical component. These would typically be nonsearchable, noncodifiable, and nondigital attributes (Lal and Sarvary 1999). For instance, consider a suitcase. Its weight is a vertical attribute that is easy for the seller to express and for the platform to learn. However, there are many other design elements that affect vertical attributes, such as the ease of use and durability of the suitcase, that the seller would know about but the platform cannot observe; for instance, the suitcase might have a novel wheel mechanism, a sturdier zipper, or a foldable handle that does not get stuck while folding. Such improvements are continually introduced into products, and the platform can learn about them through consumer reviews; however, this learning mechanism takes time, and by then, a new improvement may be introduced that the platform may again not know of. Essentially, our assumption is that there is *some* relevant information about the vertical aspects of the product that the seller knows but the platform does not know. Previous work on third-party sellers on retail platforms has made this assumption; for instance, Jiang et al. (2011) is based on the premise that a seller's product has high or low quality which the platform wants to learn but cannot always learn. Abhishek et al. (2020) also demonstrates empirically that there is information asymmetry between the seller and the platform where the seller has private information on the product being sold that is relevant to the platform. Furthermore, in conversations with us, managers at Amazon, Alibaba, Zomato, and Flipkart have revealed that, notwithstanding the massive amounts of data that platforms collect, they typically do not have all the relevant data for a product. For ease of reference, we call the seller's private information on such vertical aspects as "product quality" and denote it by $q_i, i \in \{1,2\}$, where q_i follows the uniform distribution $U[0,1]$; this distribution is common knowledge. Because information on learnable vertical aspects of a product is common knowledge, for simplicity of the model, we do not consider this type of information and assume this component away to zero.

Next, from a horizontal perspective, the platform holds some private information about consumers' idiosyncratic preferences that are not reflected in the search query. This is a natural assumption considering that the platform is collecting and analyzing massive amounts of consumer data (purchase history across multiple categories, demographics, etc.). Such consumer-level data are considered highly valuable for a platform and are rarely shared with independent sellers. We call this "personal fit" and denote it by $\lambda_{ki}, i \in \{1,2\}$, where λ_{ki} follows the uniform distribution $U[0,1]$; this distribution is common knowledge.[7]

Overall, both the vertical aspect and the horizontal aspect matter for the match value between a consumer and a product. We assume that the match value is either one or zero, denoting "match" and "no match," respectively. The match value is distributed Bernoulli(m_{ki}), where m_{ki} is the match probability between the consumer and the product.

We assume that m_{ki} is a linear combination of the vertical aspect q_i and the horizontal aspect λ_{ki}. However, which aspect is more salient for a consumer in finding a match is stochastic. In particular, we denote by θ_k the relative sensitivity that consumer k places on the vertical aspect versus the horizontal aspect in deriving consumption utilities. We assume that θ_k follows the uniform distribution $U[0,1]$; this distribution is common knowledge. The uncertainty in θ_k can stem from real-time environmental factors that affect a consumer's subjective judgment, or other information a consumer has been exposed to beyond the seller and the platform.[8] This also suggests that the same consumer can have a different realization of θ_k each time they search using a keyword, and it would be difficult for the marketplace to learn it in real time; thus, we assume that θ_k is consumer k's private information. Combined, the match probability between consumer k and product i is

$$m_{ki} = \theta_k\, q_i + (1 - \theta_k)\, \lambda_{ki},$$

where the realizations of q_i, λ_{ki}, and θ_k are independent, and they are the seller's, the platform's, and the consumer's private information, respectively. The uniform $U[0,1]$ distribution of q_i, λ_{ki}, and θ_k ensures that the combined match probability m_{ki} is also a value between zero and one. Figure 1 summarizes the information structure.

3.2. Players' Interactions and Payoffs

The platform shows both organic results and sponsored results (i.e., search ads) to the consumers. For simplicity, we consider one sponsored slot and one organic slot, where the sponsored slot is auctioned away between the sellers. Given two sellers, this is the minimal configuration that allows us to develop our insights. Our results will not change if we allow for multiple advertising or organic slots (we provide more details later in the analysis).

Table 1 shows the possible configurations for the organic listing when seller i wins the ad auction (without loss of generality, we assume that the sponsored slot is placed above the organic slot in the ladder of results): In Scenario (a), seller i is also in the organic slot, whereas in Scenario (b), seller $j \neq i$ is in the organic slot. Sellers' bidding decisions in the search ad auction may reveal their private information about product quality, that is, reveal information about q_i; we denote the revealed information by $\tilde{q}_i$. This information, in

Figure 1. Information Structure

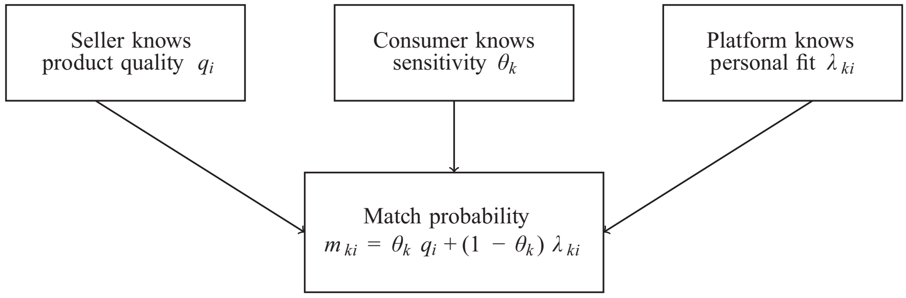


Table 1. Possible Organic Placements When Seller i Wins the Advertising Auction

Scenario (a)	Scenario (b)
Ad: Seller i	Ad: Seller i
Organic: Seller i	Organic: Seller $j \neq i$

turn, can be exploited by the platform—the platform can determine placement in the organic list using product quality inferred from sellers' bids $\tilde{q}_i$ and its own personal fit information λ_{ki}. Specifically, the platform can place in the organic slot the seller with the higher value of

$$T\tilde{q}_i + (1 - T)\lambda_{ki},$$

where T is the information weight or information sharing parameter. This parameter is optimally decided by the platform and determines the relative weight the platform places on the product quality information that it learns from the auction ($\tilde{q}_i$) and the personal fit information it already has (λ_{ki}).[9] If $T = 1$, organic ranking is completely determined by the platform's inference of the sellers' qualities from their bids, and if $T = 0$, organic ranking is independent of sellers' bids. One can think of the information weight T as a choice that a platform makes and encodes into its ranking algorithm for organic results.

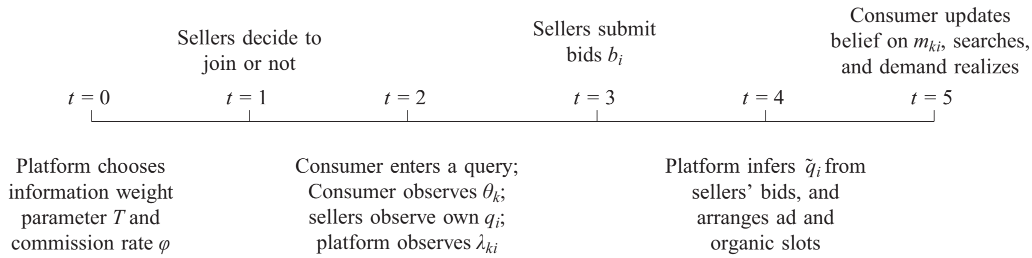
The platform has revenue from two sources: (i) commissions on sales and (ii) revenue from advertising. For each product sold, the platform charges a commission that corresponds to a percentage $\phi \in [0, 1]$ of the transaction revenue. In addition, the ad shown in the sponsored slot generates revenue. We assume that the platform uses a second-price auction with a pay-per-impression payment rule, wherein a seller whose ad is displayed pays the bid of the loser as the advertisement fee whenever a consumer searches the keyword and the seller's link is displayed. Our results remain qualitatively the same for the pay-per-click payment rule, wherein a seller pays the advertisement fee only when its link is clicked by the consumer (see Section OA1.4 in the online appendix for details).

We normalize the consumer's utility from consuming a product if a match is found to one; if there is no match, the consumption utility is zero. Mathematically, we denote by v_{ki} consumer k's consumption utility of firm i's product, where $v_{ki} \in \{1, 0\}$. Because, as described earlier, the probability of a match is given by m_{ki}, we obtain $\Pr(v_{ki} = 1) = m_{ki} \in [0, 1]$. Note that the variation in consumers' consumption utilities for a product is captured by the probability of a match, but there is no heterogeneity in the consumption utility conditional on a match.

After conducting a search, consumers need to inspect the product's page by clicking on a product's link on the search result list. We assume that consumers examine only one product before making a purchase decision. Consumers can infer their match probabilities with different sellers, taking into account sellers' placements in both advertising and organic listings, and click on the seller with the highest expected match probability. Suppose the consumer chooses to click on seller i and denote the selling price of product i as p_i. Then the consumer purchases product i if and only if her net payoff, $v_{ki} - p_i$, is no less than her outside option of zero. Because the realization of v_{ki} has a value of either zero or one, a seller will optimally set his selling price p_i equal to one. In equilibrium, if a match is found (i.e., v_{ki} realizes as one with a probability of m_{ki}), the consumer purchases product i. If there is no match (i.e., v_{ki} realizes as zero with a probability of $1 - m_{ki}$), the consumer exits the platform and takes the outside option. In either case, the consumer obtains a net payoff of zero, so that the platform and the sellers will split all surplus. We adopt this modeling strategy to prevent pricing decisions from confounding the analysis and to focus on the interaction between the advertising and selling decisions of the players. It is important to realize that this formulation is consistent with a model where consumers' expected consumption utility, that is, $E(v_{ki})$, is a function of revealed information (i.e., it reflects the probability of a match) and, yet, firms always price their products equal to consumers' consumption utility conditional on a match, which is constant (and equal to one). We acknowledge that by assuming that consumers examine only one product with zero search cost, the current model abstracts away from price competition.[10]

Each seller has an exogenous outside option of value u_0 for selling his product. For example, the seller could sell through his online store directly rather than selling via the platform. As discussed earlier, if the seller decides to use the platform, he pays a commission ϕ to the platform on the total transaction revenue. Sellers can also advertise their products on the platform's search engine using the second-price pay-per-impression auction, as discussed earlier. We assume the marginal cost of the products to be zero for both sellers. Therefore, the two sellers are ex ante symmetric.

Figure 2. Timing of the Game



3.3. Timing of the Game

The timing of the game is illustrated in Figure 2. First, at $t = 0$, the platform decides the commission rate ϕ and the information weight parameter T. Observing T and ϕ, at $t = 1$, each seller makes his decision to join the platform or not; to join, a seller compares his expected profit from selling on the platform to the outside option u_0. If there is at least one seller, the game proceeds, and at $t = 2$, a consumer enters a search query. The consumer privately observes the realized value of her sensitivity, θ_k; sellers privately observe the realized value of their product quality, q_i;[11] and the platform observes the realized value of personal fit, $\lambda_{ki}, i \in \{1,2\}$. At $t = 3$, the sellers simultaneously submit their bids b_i. At $t = 4$, the platform places the winner of the ad auction in the sponsored ad slot. This is followed by an organic slot, the occupant of which can be influenced by the information revealed during the ad auction. In particular, the platform infers $\tilde{q}_i$ from sellers' bids and places the seller with a higher $T\tilde{q}_i + (1 - T)\lambda_{ki}$ in the organic slot.[12] Finally, at $t = 5$, consumers see sellers' placements in both sponsored and organic listings. They update their expected match probabilities with different sellers, m_{ki}, by taking into account sellers' placements, and click on the seller with the highest expected match probability. Upon search, consumers observe the realization of the match value with the seller they choose to examine and purchase if and only if they find a match. We solve the game using backward induction.

We note that we assume that the platform can commit to ϕ and T. The value of ϕ, which is the commission rate on sales, can be specified in a contract and so can be committed to. The value of T, which is the information weight parameter that determines how the platform uses the information learned from the ad auction, is a choice that the platform makes. To operationalize this, the platform encodes the choice into its ranking algorithm, which is a longer-term action than a seller's decision to join the platform or not. Therefore, our assumption about the ability to commit to T is essentially the assumption that a seller's decision to join the platform and determine a bid for the ad auction is more flexible and easier to revise than the platform's choice and encoding of the information weight parameter into its ranking algorithm. In other words, we assume that it is easier for sellers to react to the platform's algorithm than for the algorithm to react to the sellers' actions.[13]

4. Analysis

The following is the outline of the analysis. The sellers' bids will depend on how the platform determines the organic listing conditional on the bids, and how consumers search given an arrangement of the sponsored and organic listings, which in turn depend on how sellers bid. We first derive, in Section 4.1, sales outcomes given each arrangement of sellers' listings and sellers' bidding strategies. In Section 4.2, we determine the implications on the platform's commission revenue and advertising revenue. In Section 4.3, we derive implications for optimal marketplace design wherein we consider the choice of commission rate and the optimal information weight while accounting for the sellers' participation on the marketplace. We note that it suffices to focus on the parameter space with $0 \leq T \leq 1$, which generates the highest possible revenue for the platform (see Section OA1.5 in the online appendix for the results with $T < 0$ and $T > 1$).

4.1. Consumer Choice and Sellers' Advertising Bids

We solve for consumer click choice and sellers' advertising bids by assuming that the seller's bid function $b(q_i)$ strictly increases in q_i; we will verify this assumption later. Under this assumption, the platform can infer the true value of q_i from sellers' bids based on $b^{-1}(\cdot)$, and it places the seller with the higher $T \cdot q_i + (1 - T) \cdot \lambda_{ki}$ in the organic result. Consumers can infer that, first, the winner of the ad auction has a higher product quality q_i, and second, the seller in the organic result has a higher $T \cdot q_i + (1 - T) \cdot \lambda_{ki}$, and click accordingly. Finally, to justify our assumption, we need to verify that when consumers click according to their expectation that $b(q_i)$ strictly increases with q_i, the seller with the higher-quality product will indeed bid higher.

4.1.1. Consumer Choice. We first derive the demand realization corresponding to each arrangement of the sellers' listings as in Table 1. Given an arrangement of the sellers' listings, consumers can update their expectations about their match probabilities with each seller and click on the seller with the higher expected match probability.

Scenario (a). In this scenario, the same seller appears in the ad slot and the organic result, and he sells to all consumers. Intuitively, if seller i obtains both the ad slot and the organic slot, it implies that $q_i > q_j$ and $Tq_i + (1-T)\lambda_{ki} > Tq_j + (1-T)\lambda_{kj} \Rightarrow \lambda_{ki} > \lambda_{kj} - \frac{T}{1-T}(q_i - q_j)$; that is, seller i is the higher-quality seller, and his individual fit is comparable with that of seller j. This makes seller i more attractive for all consumers (see Section A.1 in the Appendix for the detailed proof). We note that even if the other seller's link is shown in a second organic slot, conditional on the same seller appearing in the ad slot and in an organic slot, none of the consumers will click on the second organic slot. Therefore, our results will not change even if we allow for multiple organic slots.

Scenario (b). Under this scenario, seller i wins the ad slot but seller j gets placed in the organic slot, implying that $q_i > q_j$ and $Tq_i + (1-T)\lambda_{ki} < Tq_j + (1-T)\lambda_{kj}$. If the consumer clicks on seller i, she expects a matching probability of $\mathbb{E}_{q_i,\lambda_{ki},q_j,\lambda_{kj}}[m_{ki} | q_i > q_j, Tq_i + (1-T)\lambda_{ki} < Tq_j + (1-T)\lambda_{kj}]$. If she clicks on seller j, she expects a match probability of $\mathbb{E}_{q_i,\lambda_{ki},q_j,\lambda_{kj}}[m_{kj} | q_i > q_j, Tq_i + (1-T)\lambda_{ki} < Tq_j + (1-T)\lambda_{kj}]$. The match probability with seller i is higher than that with seller j if and only if $\theta_k \le \theta^T$, where

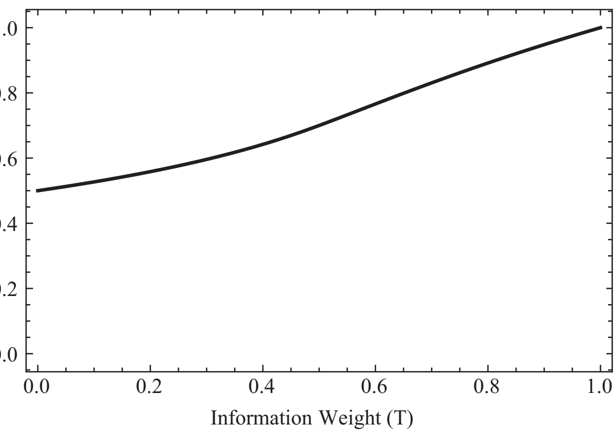
$$\theta^T = \begin{cases} \dfrac{10 - 30T + 25T^2 - 3T^3}{20 - 70T + 78T^2 - 26T^3}, & 0 < T \le \dfrac{1}{2}, \\ \dfrac{T(-3+13T)}{-2+6T+6T^2}, & \dfrac{1}{2} < T \le 1. \end{cases} \tag{1}$$

Section A.1 in the Appendix gives the proof for this. Intuitively, under Scenario (b), although seller i has the higher-quality product, seller j has a better personal fit. As a result, consumers with high preferences for product quality click on seller i in the ad slot, and consumers with high preferences for personal fit click on seller j in the organic slot. Combining the previous analyses, we summarize the consumers' clicking behavior in the following lemma.

Lemma 1. *If the same seller appears in the sponsored and the organic slots, then this seller is the preferred seller for all consumers, and all consumers click on either one of the links of this seller. If different sellers appear in the sponsored and the organic slots, consumers with $\theta_k > \theta^T$ click on the sponsored slot, whereas consumers with $\theta_k \le \theta^T$ click on the organic slot, where θ^T is as specified in* (1).

Figure 3 illustrates the preference of the consumer who is indifferent between clicking on the ad slot and the organic slot under Scenario (b). As T increases and sellers' advertising bids influence organic ranking more heavily, the cutoff value θ^T also increases, suggesting that more consumers will click on the organic slot, which shows a different seller than the ad slot. This is because as T increases, it becomes more difficult for the lower-quality seller j to obtain the organic slot. If seller j indeed gets the organic slot, consumers will lower their expectation for seller i's personal fit. Consequently, fewer consumers will click on seller i and more consumers will click on seller j.

Figure 3. Cut-Off Value of θ^T in Consumer Choice



4.1.2. Sellers' Advertising Bids. Given the demand distribution in each configuration, we can now assess sellers' optimal bidding strategies for the advertising slot under the pay-per-impression second-price auction. We need to verify that under the consumer choice derived previously, the bid function $b(q_i)$ indeed increases with product quality q_i. At this stage, we assume that the commission rate ϕ is fixed.

Under the Bayesian Nash equilibrium, if a seller with product quality q_i deviates from bid $b(q_i)$ to bid $b(q_i')$, then we can write his expected profit as follows:

$$\begin{aligned} U_{q_i}(q_i') = & \int_0^{q_i'} \mathbb{E}_{\lambda_{ki},\lambda_{kj},\theta_k} \\ & \left[(1-\phi)\, m_{ki}\, 1_{\{Tq_i'+(1-T)\lambda_{ki} > Tq_j+(1-T)\lambda_{kj}\}}\right] dq_j \\ & + \int_0^{q_i'} \mathbb{E}_{\lambda_{ki},\lambda_{kj},\theta_k > \theta^T} \\ & \left[(1-\phi)\, m_{ki}\, 1_{\{Tq_i'+(1-T)\lambda_{ki} < Tq_j+(1-T)\lambda_{kj}\}}\right] dq_j \\ & + \int_{q_i'}^{1} \mathbb{E}_{\lambda_{ki},\lambda_{kj},\theta_k < \theta^T} \\ & \left[(1-\phi)\, m_{ki}\, 1_{\{Tq_i'+(1-T)\lambda_{ki} > Tq_j+(1-T)\lambda_{kj}\}}\right] dq_j \\ & - \int_0^{q_i'} b(q_j) dq_j. \end{aligned}$$

The first term represents seller i's revenue when he obtains both the ad slot and the organic slot and, as a result, all consumers click on seller i. This happens when $q_i > q_j$ and when seller i also obtains the organic result under $Tq_i' + (1-T)\lambda_{ki} > Tq_j + (1-T)\lambda_{kj}$. The second term represents seller i's revenue when he obtains only the ad slot and, therefore, sells to consumers with $\theta_k > \theta^T$. This happens when $q_i' > q_j$, and when seller j obtains the organic slot under $Tq_i' + (1-T)\lambda_{ki} < Tq_j + (1-T)\lambda_{kj}$. The third term represents seller i's net profit when he obtains only the organic slot and thus sells to consumers with $\theta_k < \theta^T$. The condition required is that seller j wins the auction, when q_j is larger than q_i', and seller i obtains the organic result under $Tq_i' + (1-T)\lambda_{ki} > Tq_j + (1-T)\lambda_{kj}$. Finally, when seller i fails to obtain either the ad slot or the organic slot, there is no demand for seller i. As for the ad payment, under the assumption that a seller's bid increases with his quality, seller i wins the ad auction when $q_i' > q_j$, and he pays seller j's bid $b(q_j)$.

The seller's expected profit is maximized at $q_i' = q_i$. Due to the complexity of the analysis to show this, we provide the details in Section A.2 in the Appendix. We state the following lemma.

Lemma 2. *The seller's optimal bid, $b(q_i)$, is given in* (A.9) *(in Section* A.2 *in the Appendix).*

Here, we discuss some key properties of the bidding function. In terms of the curvature of $b(q_i)$, we can show that $b(q_i)$ is a cubic function of q_i. Furthermore, $b(q_i)$ is strictly increasing and concave over $q_i \in [0,1]$ given $T \le \bar{T}$, where $\bar{T} = 0.5$ under our distributional assumptions. Intuitively, $b(q_i)$ increases with q_i because bidding higher increases the probability of winning both the ad slot and the organic slot, and the gain from obtaining either slot is more substantial for the seller with higher q_i. The fact that $b(q_i)$ is concave over q_i suggests that a seller's bid grows with q_i at a slower speed when q_i increases. This relates to the interaction between obtaining an ad slot and an organic slot. A seller with large q_i will have a significant chance to obtain and sell through the organic slot, thus indirectly reducing his incentive to obtain the ad slot.

If $T > \bar{T}$, there does not exist a pure strategy equilibrium in the bidding game.[14] However, in Section A.2 in the Appendix we show that a mixed strategy equilibrium exists in this region and the profit of the platform in any such equilibrium is always lower than the maximum profit that the platform makes for $T \le \bar{T}$. Intuitively, the reason is that, in this region, the total possible surplus that can be generated by the transaction (even if q_1 and q_2 were perfectly known) is smaller than the platform's equilibrium profit for $T = \bar{T}$ (where a pure strategy equilibrium for the bidding game does exist); therefore, for $T > \bar{T}$, the platform's profit must be lower than its profit for $T = \bar{T}$. For $T \le \bar{T}$, we confirm that $b(q_i)$ increases with q_i, so the seller with the higher-quality product will win the ad auction; this aligns with our initial assumption of the analysis.

The other scenario in which the seller with the lower-quality product wins the ad auction cannot be supported in equilibrium. Indeed, if consumers expect the lower-quality seller to win the ad auction and click accordingly, winning the ad auction will lead to lower sales for a seller compared with losing the ad auction. This is because if bidding higher for the ad implies lower product quality, identifying that the winner of the ad auction sells the lower-quality product, consumers will be less likely to click on the product. Expecting that winning the ad slot will lead to lower sales, neither seller will bid positively for the ad slot. This contradicts the assumption that the seller with the lower-quality product wins the ad auction. Given the preceding arguments, we state the following lemma.

Lemma 3. *To maximize its profit, the platform will choose $T \le \bar{T} = 0.5$.*

Given Lemma 3, we focus our discussion on the parameter space $T \le \bar{T}$. The result that a seller's bid increases with q_i aligns with the literature on search advertising with endogenized consumer search. For instance, Armstrong et al. (2009) show that the seller with the highest value for consumers also has the greatest incentive to become prominent. Athey and Ellison (2011) show that for search ads, the most relevant advertisements will be promoted to the top. The key intuition behind these papers—and also here—is that consumers rationalize their search strategies based on expected bidding outcomes. If winning the ad slot reveals that a seller is of lower quality, then he will attract fewer clicks and obtain less profit; this reduces the seller's incentive to bid high in the first place.

Combining all of the previous analyses, we conclude that, given $T \le \bar{T}$, the seller with the higher-quality product wins the ad auction in equilibrium. The following proposition summarizes this result.

Proposition 1 (Consumer Choice and Sellers' Advertising Bids). *Given any information weight $T \le \bar{T}$ and commission rate ϕ, the seller with the higher-quality product wins the ad auction. If consumers find the same seller in the ad slot and the organic slot (Scenario* (a)*), then all consumers click on this seller. If consumers find different sellers in the ad slot and in the organic slot (Scenario* (b)*), then consumers with $\theta_k \ge \theta^T$, where θ^T is as specified in* (1)*, click on the ad slot, whereas consumers with $\theta_k < \theta^T$ click on the organic slot. The expected demands in the two scenarios are specified in Table* 2.

Table 2. Expected Demand Given Each Arrangement of Sellers' Listings

	Scenario			
	(a)		(b)	
Listings	Seller	Demand	Seller	Demand
Ad	i	1	i	$1-\theta^T$
Organic	i	0	j	θ^T

4.2. Platform's Sales Commission Revenue and Advertising Revenue

Having solved for the consumer search strategy and the bidding game, we can assess the impact of strategic listing on the platform's two streams of revenue, that is, the sales commission revenue and the advertising revenue. Let $D(T)$ denote the demand at the platform for a given value of the information weight parameter T. Given the commission rate ϕ, the sales commission revenue of the platform is given by $\phi D(T)$. The advertising revenue of the platform is given by $2\int_0^1\int_0^{q_j} b(q_i)\,dq_i\,dq_j$. In Section A.3 in the Appendix, we derive the expressions for both of these revenues, given the commission rate ϕ and an information weight parameter T, by integrating over the possible realizations of q_i, q_j, λ_{ki}, λ_{kj} and θ_k. We state the following lemma.

Lemma 4. *The platform's sales commission revenue is given by* (A.10)*, and the platform's advertising revenue is given by* (A.11).

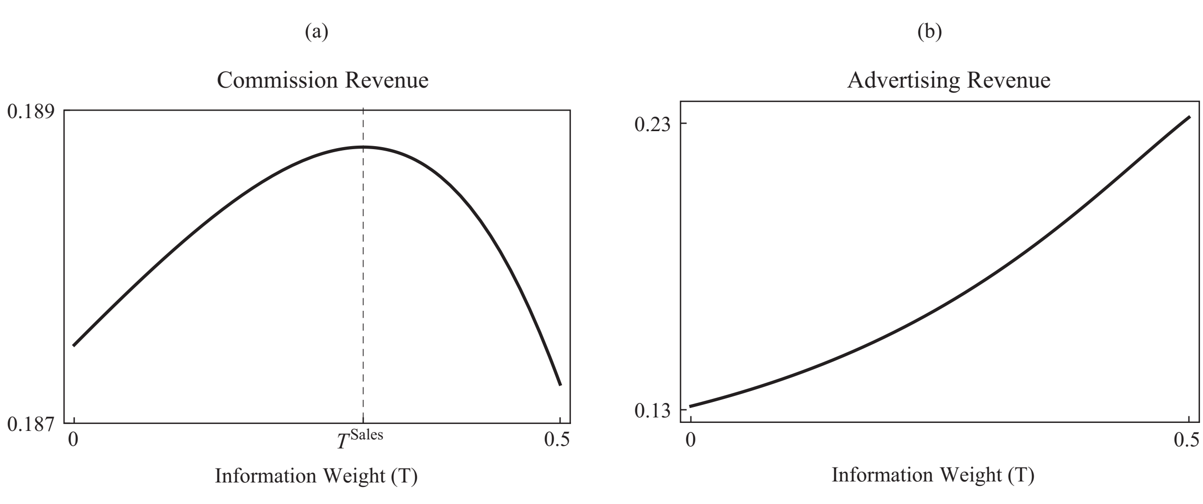
Now, we proceed to evaluating the effect of T on the platform's two sources of revenue, that is, revenue from sales commissions and ads. We state the result in the following proposition and illustrate it in Figure 4.

Proposition 2 (Effect of Information Weight Parameter T on Platform Revenue). (a) *The platform's sales commission revenue first increases and then decreases in T. The sales commission revenue is maximized at an intermediate value of T, which we denote by T^{Sales}; under our distributional assumptions, $T^{Sales} = 0.3$.* (b) *The platform's advertising revenue increases in T.*

To provide intuition for these outcomes consider the sales commission revenue first. Strategic listing can facilitate consumer purchase, as advertising bids reveal sellers' information about their product quality, which can in turn be exploited by the marketplace to promote sellers with better match for an average consumer. Given a fixed commission rate, the platform's commission revenue is maximized when the expected demand $D(T)$ is the highest, which happens at the intermediate value $T^{Sales} = 0.3$ (see Figure 4(a)). This is because if T is too small and the ranking function is heavily biased toward personal fit, then the consumers will not be able to benefit from the product quality information revealed from sellers' bids. On the other hand, if T is too large and the ranking function is heavily biased toward product quality, customers will not be able to benefit from the personal fit information that the marketplace has; this also results in worse match between sellers and consumers. Overall, the total expected product sales are maximized at $T = T^{Sales}$, when sellers' bids have a moderate influence on organic rankings. We call this the information effect of strategic listing.

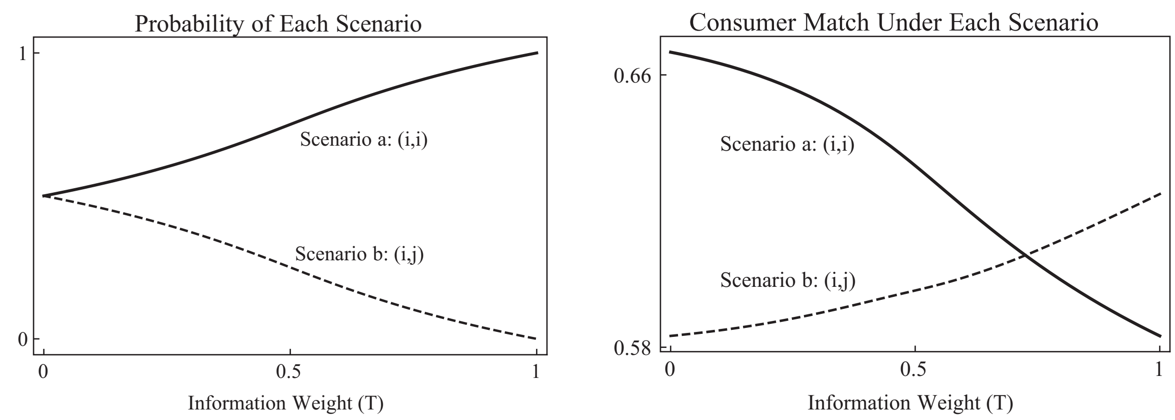
We further explain the information effect of strategic listing by breaking down the expected demand given a possible organic placement. The left panel of Figure 5 shows that as T increases, Scenario (a) is more likely to happen, and Scenario (b) is less likely to happen. However, the right panel of Figure 5

Figure 4. Effect of Strategic Listing on Platform's Revenue



Note. $\phi = 0.3$.

Figure 5. Consumer Match Given Information Weight T



shows that the expected consumer match, $D(T)$, decreases with T given Scenario (a), and it increases with T given Scenario (b). The reason is as follows. As T increases, Scenario (b) reveals more information about the two sellers' personal fit to consumers—the fact that seller j obtains the organic slot, even when it has a low product quality and the low product quality tends to lower its organic position, reveals that it must have a high personal fit. In contrast, as T increases, Scenario (a) reveals less information about the two seller's personal fit, that is, it gets more difficult to tell whether seller i obtains the organic slot because of its high product quality or because of its personal fit. Overall, when T increases from a small value, the effect of improving consumer match in Scenario (b) dominates. When T increases beyond T^{Sales} and Scenario (b) becomes less likely to happen, the effect of worsening consumer match in Scenario (a) dominates. In other words, consumer demand presents an inverted-U shape with T and is maximized at T^{Sales}.

Turning to the platform's advertising revenue, increasing T increases the probability for the winner of the ad auction to be placed in the organic slot, thus increasing the value of winning the ad slot for sellers. Essentially, the practice of strategic listing (i.e., if $T > 0$) exerts an externality influencing the bids in the ad auction because the outcome of the auction influences not only which seller is placed in the sponsored slot, but also influences which seller is placed in the organic slot. Mathematically, the seller's bid $b(q_i)$ increases with T for $T \le \bar{T}$. Therefore, the platform's advertising revenue also increases in T (see Figure 4(b)). We call this the competition effect of strategic listing.

To summarize, strategic listing influences both the sales commission revenue and the advertising revenue. In the next section, we discuss how the platform balances the effects on these two revenue streams to maximize its total revenue.

4.3. Platform's Design Decisions

After a discussion of the impact of the platform's strategic listing on sellers, consumers, and its own revenue sources, we now turn to the question of optimal marketplace design, that is, the platform's optimal choices of the commission rate and the information weight parameter. In the following, we first obtain insights regarding the platform's choice of commission rate under a fixed strategic listing strategy (i.e., for a fixed value of the information sharing parameter T). Following this, we make the sellers' decision to join the platform endogenous and jointly derive the optimal commission rate and listing strategy.

4.3.1. Platform's Choice of Commission Rate. We observe very different commission rates across platforms operating in different geographies. For example, whereas Alibaba charges a commission rate of 0%–5% for each transaction, Amazon charges a commission rate of approximately 15% for popular product categories. What might drive the choice of the optimal commission rate? In this section, we aim to answer this question by analyzing how the platform optimally chooses a commission rate under a fixed listing strategy.

We investigate how the platform's revenue changes with its commission rate, ϕ, by fixing the platform's information weight and assuming that sellers participate. We can then write the platform's expected profit $\Pi\,(T,\phi)$ as a function of its commission rate ϕ and information weight T:

$$\Pi(T,\phi) = \underbrace{\phi D(T)}_{\text{Sales commissions}} + \underbrace{2\int_0^1 \int_0^{q_j} b(q_i)\, dq_i\, dq_j}_{\text{Advertising revenue}}.$$

The first term accounts for the platform's commission revenue (where the platform's commission rate, ϕ, appears as a multiplier). The second term accounts for the platform's ad revenue (which appears as a multiplier of $1-\phi$, as Section A.3 in the Appendix shows). Therefore, a higher commission rate leads to higher revenue through commissions but lower revenue through advertising. The latter is because sellers bid lower when the platform takes a larger proportion of their revenue. Overall, taking derivatives of the platform's revenue Π with respect to the commission rate ϕ, we have $\frac{\partial \Pi(T,\phi)}{\partial \phi} > 0$. This implies that if the platform charges a higher commission rate, the loss in the revenue from advertising is smaller than the gain in revenue from commissions. The intuition is that the platform earns commission revenue from both the ad slot and the organic slot, whereas it earns advertising revenue only from the ad slot. Thus, the increase in commission revenue dominates the losses in ad revenue for the platform when ϕ increases. The following lemma states this result.

Lemma 5. *Given a fixed information weight and assuming the sellers' participation, the platform's total revenue increases with the commission rate, ϕ.*

Next, we allow sellers to endogenously decide whether they want to participate on the platform, given that they have an outside option u_0. Given this, we determine the optimal sales commission rate that the platform charges (still assuming an exogenous information weight parameter). Recall that at the time the sellers make their participation decisions, they do not know the realization of their products' match probabilities and are therefore identical in every way. Therefore, both sellers face the same participation constraint and the platform must choose its commission rate to maximize its profit while considering the sellers' participation. Because the platform's profit increases with the commission rate ϕ (Lemma 5), at the optimum, the platform sets its commission rate to make the sellers' participation constraint binding, extracting all the surplus from the sellers. In particular, the seller's net profit under a fixed commission rate ϕ and information weight T can be written as

$$U(T,\phi) = \underbrace{(1-\phi)\frac{1}{2}\,D(T)}_{\text{Each seller's expected sales revenue}} - \underbrace{\int_0^1 \int_0^{q_j} b(q_i)\,dq_i\,dq_j}_{\text{Each seller's expected advertising payment}}.$$

Then, given an information weight T, the commission rate to extract the full surplus of the sellers is $\phi^* = 1 - \frac{u_0}{U(T,0)}$, where $U(T,0)$ is a seller's profit given the information weight T and zero commission rate defined previously. The detailed solution is given in Section A.3 in the Appendix. The following lemma states this result.

Lemma 6. *Given a fixed information weight T, the platform sets the commission rate $\phi^* = 1 - \frac{u_0}{U(T,0)}$ to make the sellers' participation constraint binding, extracting the full surplus of the sellers.*

Based on Lemma 6, the optimal commission rate, given sellers' outside option u_0, decreases with the information weight T. This is because given a particular commission rate, sellers' profit decreases with T, as a larger T leads to higher bids in the auction, therefore increasing the advertising fees. Having derived these results and insights, we now proceed to the final step of jointly determining both the information weight parameter and the commission rate.

4.3.2. Endogenous Information Weight and Commission Rate.

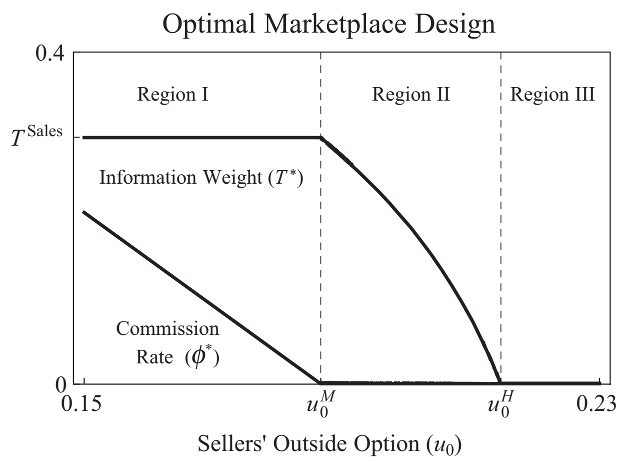
In this section, we jointly determine the platform's marketplace design parameters, specifically, the optimal sales commission rate and the information weight parameter. To simplify notations, define $u_0^M \equiv U(T^{Sales},0)$, $u_0^H \equiv U(0,0)$. We first state the main finding in the following proposition and illustrate it with the help of Figure 6.

Proposition 3 (Optimal Information Weight Parameter and Sales Commission). *If sellers' outside option is small ($u_0 \le u_0^M$), the optimal information weight is $T^* = T^{Sales}$; in this region, the optimal commission rate is $\phi^* = 1 - \frac{u_0}{u_0^M}$, and it decreases as sellers' outside option increases. If the sellers' outside option is intermediate ($u_0^M < u_0 \le u_0^H$), the optimal information weight T^* decreases from T^{Sales} to zero as sellers' outside option increases; in this region, the optimal commission rate is $\phi^* = 0$. If the sellers' outside option is large enough ($u_0 > u_0^H$), sellers do not participate under any choice of information weight and commission rate.*

Based on Proposition 3, the platform's information weight parameter, T^*, is strictly positive as long as u_0 is not too large, that is, the platform benefits from strategic listing. Intuitively, exploiting ad information to refine organic ranking can enable the platform to present a seller with a better match to the average consumer, thus facilitating consumer purchase and benefiting the marketplace (the information effect). In Region I of Figure 6, where the sellers' outside option is small, the platform sets $T^* = T^{Sales}$ to maximize product sales. Meanwhile, the platform sets its commission rate ϕ^* at the highest level while ensuring the sellers' participation, which makes the sellers' participation constraint binding, extracting all the surplus from sellers (over and above the outside option). The optimal commission rate $\phi^* = 1 - \frac{u_0}{u_0^M}$ decreases with u_0 as it becomes more difficult to incentivize sellers' participation.

When u_0 increases beyond u_0^M (Region II), even if charging zero commission rate, the sellers' participation cannot be ensured if the marketplace sets

Figure 6. Optimal Marketplace Design



$T = T^{Sales}$. As a result, the platform needs to rank organic results more based on its existing information about personal fit, and less based on sellers' advertising bids. This helps reduce the advertising competition between sellers and incentivize sellers' participation (i.e., lower the competition effect). In particular, the platform charges zero commission rate, thus earning zero commission revenue. Furthermore, it chooses the highest possible T to maximize advertising revenue while ensuring sellers' participation. The optimal information weight in this region gradually decreases from T^{Sales} to zero, as u_0 increases from u_0^M to u_0^H.

As u_0 increases beyond u_0^H (Region III), sellers will not participate even if the platform charges zero commission rate and sets $T = 0$. Recall that given a fixed commission rate, a seller's net profit is maximized at $T = 0$. This suggests that in Region III, seller participation cannot be ensured by any combination of commission rates and information weights.

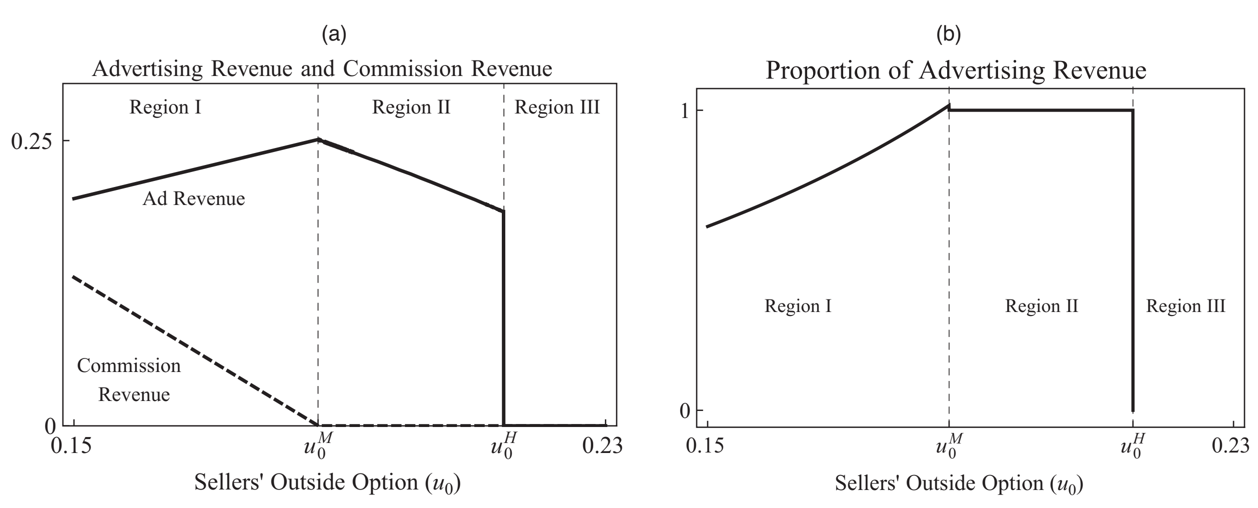
To further understand the result, we discuss the platform's two streams of revenues under the optimally chosen information weight and commission rate. The findings are presented in Corollary 1 and Figure 7.

Corollary 1 (Platform's Revenue Under Optimal Marketplace Design). *If sellers' outside option is small ($u_0 \leq u_0^M$), the platform earns less commission revenue and more advertising revenue as sellers' outside option increases. If the sellers' outside option is intermediate ($u_0^M < u_0 \leq u_0^H$), the platform makes zero commission revenue and relies entirely on advertising revenue. If the sellers' outside option is large enough ($u_0 > u_0^H$), the platform makes zero commission revenue and zero advertising revenue.*

Figure 7(a) plots the platform's advertising and commission revenues, respectively, and Figure 7(b) plots the platform's advertising revenue as a fraction of its total revenue. Based on Figure 7(a), in Region I, the platform makes less commission revenue, as it responds to an increase in the sellers' outside option by lowering the commission rate ϕ^* (see Proposition 3). However, the lowered commission rate increases a seller's sales margin and prompts them to bid higher. This translates into high advertising revenue for the platform. Combined, the platform derives a strictly larger proportion of revenue from advertising as u_0 increases, as Figure 7(b) shows.

In Region II, the platform makes zero commission revenue because it charges zero commission rate. The platform's advertising revenue also starts to decline, as it relies less on sellers' advertising bids to rank the organic results to reduce sellers' advertising competition. In this region, we have an extreme outcome

Figure 7. Platform Revenue Streams Under Endogenous Commission Rate



where the platform relies entirely on advertising revenue, even though the absolute amount of advertising revenue decreases with u_0. In Region III, the platform makes zero revenue because sellers do not participation.

Across the three regions, Figure 7(b) shows that the platform relies (weakly) less on commission revenue and (weakly) more on advertising revenue as a fraction of its total revenue as the sellers' outside option increases. The intuition behind this is as follows. As sellers' outside option increases and their participation becomes more difficult to incentivize, the platform prefers reducing the commission rate (if possible) and making less commission revenue, over reducing the information weight and making less advertising revenue. This is because reducing the commission rate merely transfers surplus from the platform to sellers. However, lowering the information weight leads to less consumer demand; thus, it not only transfers surplus to sellers (competition effect) but also reduces the total surplus that can be transferred (information effect). Loosely speaking, the role of the information weight parameter is to "increase the pie," whereas the role of the commission rate is to "split the pie." Only when the commission revenue reduces to zero, the platform resorts to reducing the information weight at the cost of advertising revenue. In other words, as sellers' outside option increases, the platform prefers a reduction in the commission revenue over a reduction in the advertising revenue, thus (weakly) increasing its reliance on advertising revenue proportion-wise.

To summarize, the platform benefits from using information learned from the ad auction to improve the placement of results on the organic side. However, as our analysis shows, this is a complex decision that involves a subtle balance between different forces, and the platform must jointly utilize various levers that it has at its disposal to optimally benefit from it. The marketplace should use the information it learns from sellers' bids and the information it already has in a balanced manner to maximize product sales, and relies on adjusting the commission rate to ensure sellers' participation. As it becomes more difficult to incentivize sellers' participation, the platform should reduce both the dependence of the organic results on the information learned from sponsored ad bidding and its commission rate. Overall, as sellers' participation becomes a more pressing issue, the platform should charge a lower commission rate and rely more on advertising revenue.

5. Extensions

We now present two extensions to the main model. In the first extension, we enforce independent listing, that is, the platform does not use the information obtained from the ad auction to influence the arrangement of the organic side, and, using this as a benchmark, we study the benefit that the platform has from using strategic listing. In the second extension, we consider the case that in addition to each party's private information, each seller and the platform share some common information. We show that our insights can be extended to this scenario.

5.1. Comparison with Independent Listing

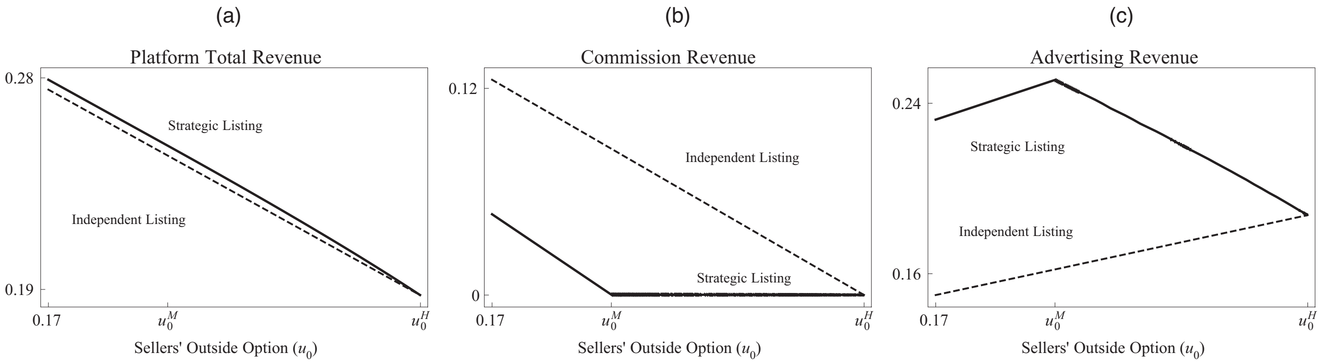
A major insight from our analysis is that the platform can benefit from strategic listing, that is, the optimal T for the platform is not zero. To isolate the benefits of making the listing strategy endogenous, in this section, we build two benchmark cases where the platform ranks organic results independently from sellers' bids, that is, the platform is forced to set $T = 0$, and compare the outcomes to the strategic listing case.

First, consider the case where the platform sets $T = 0$ but can optimize everything else (i.e., choose the optimal ϕ corresponding to $T = 0$). Not surprisingly, when the commission rate ϕ is endogenously decided, the platform's revenue from strategic listing (i.e., under the optimally chosen T^* and ϕ^* as in our main analysis) is weakly higher than that under independent listing where T is restricted to be zero in the whole parameter space. Interestingly, with endogenous commission rates, strategic listing leads to lower commission revenue for the platform (relative to independent listing). However, the losses are more than compensated by the gains in advertising revenue, and overall, strategic listing benefits the platform in the whole parameter space. Proposition 4 and Figure 8 summarize these findings.

Proposition 4 (Comparison with Independent Listing Under Endogenous Commission Rate). *With an endogenous commission rate, strategic listing leads to lower commission revenue but higher advertising revenue for the platform relative to independent listing. Overall, the platform (weakly) benefits from strategic listing in the whole parameter space.*

Figure 8, (a)–(c), depicts the differences between strategic listing and independent listing in the platform's total revenue, commission revenue, and advertising revenue, respectively, when the commission rate is optimally chosen correspondingly. When the seller's outside option is small (i.e., $u_0 \leq u_0^M$), the platform chooses $T^* = T^{Sales}$, which results in higher advertising revenue compared with $T = 0$ because of the competition effect. However, to encourage sellers' participation, the platform has to charge a lower commission rate, which results in a loss of commission revenue for the platform. Overall, the positive effect on advertising revenue outweighs the negative effect

Figure 8. Comparison Between Strategic Listing and Independent Listing Under Endogenous Commission Rate



Notes. The solid line represents the case where T is optimally chosen, and the dotted line represents the case where T is fixed at zero. In both lines, the commission rate ϕ is endogenously decided.

on commission revenue for the platform. When u_0 increases beyond u_0^M, even though strategic listing only generates advertising revenue, it is still sufficient to compensate for the commission revenue that the platform would have obtained from an independent listing.

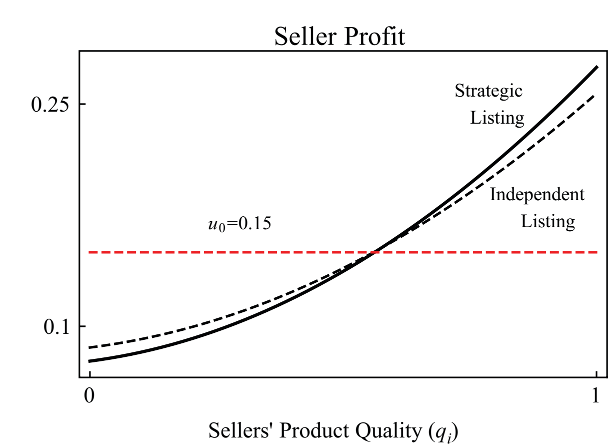
The intuition is the same as to why the optimal information weight can be strictly positive in Proposition 3. Under an endogenous commission rate, the platform can extract all surplus by adjusting ϕ corresponding to any information weight T, leaving sellers just their outside options. Because demand is higher under strategic listing and the platform can extract all surplus (beyond the seller's outside option), the platform's total revenue will also be higher under strategic listing.

As we have mentioned, sellers expect a net profit of u_0 upon joining the platform under either listing strategy. However, as sellers' qualities get realized after a consumer search, the realized seller profit can be greater than or smaller than u_0. Figure 9 further compares a seller's realized profit between strategic listing and independent listing. It shows that strategic listing helps sellers who realize a higher product quality and hurts sellers who realize a lower product quality. The reason is that strategic listing improves the organic placement of higher-quality sellers.

Note that we obtain that strategic listing leads to lower commission revenue under the current model without price competition; that is, in our model, all variations in match values are summarized by the variations in match probabilities so that both sellers price optimally at $p_i = 1$. Suppose we further allow variations in the product value conditional on a match. In that case, sellers may compete in prices, and strategic listing has the potential to soften price competition, as it leads to a favorable placement for the winner of the ad auction in both the sponsored listing and the organic listing. This would still imply that strategic listing will lead to greater platform profit than independent listing, but it may moderate our result that commission revenue is lower under strategic listing. We leave these implications to future research.

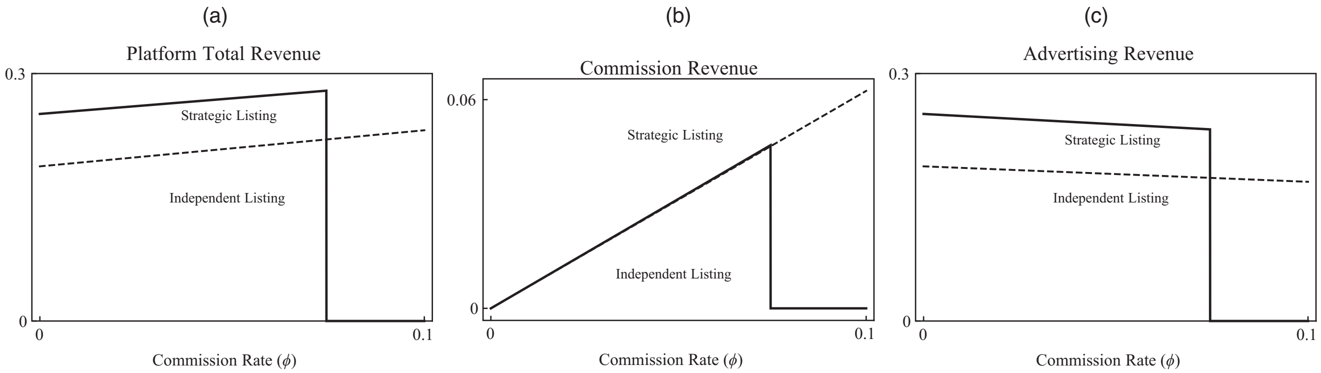
A natural question is whether our analysis can be extended to a purely informational search engine that earns only advertising revenue, yet has the option to rank organic results based on search advertising. The value of the organic listings at an informational search engine is not due to the sales revenue that they generate through commissions, but due to gradual impact on long-term factors such as repeat visits to the search engine and reputation building. In other words, the search engine cannot simply choose an optimal commission rate (or its equivalent) to optimally monetize its organic side; rather, it has to essentially treat the monetization parameters on the organic side as

Figure 9. Comparison of the Seller's Realized Profit upon Participation Between Strategic Listing and Independent Listing Under Endogenous Commission Rate



Note. The solid line represents the case where T is optimally chosen, and the dotted line represents the case where T is fixed at zero.

Figure 10. Comparison Between Strategic Listing and Independent Listing Under Exogenous Commission Rate



Notes. The seller's outside option is fixed at $u_0 = 0.175$. The solid line represents the case where T is optimally chosen at $T^* = T^{Sales}$ for $u_0 = 0.175$ according to Proposition 3, and the dotted line represents the case where T is fixed at zero.

exogenous. Furthermore, purely informational search engines such as Google explicitly promise that advertising outcomes will not influence organic results. These considerations together motivate the analysis of a scenario with independent listing (i.e., the platform is forced to set $T = 0$) and exogenously specified ϕ. We compare the platform's revenue when it sets $T = T^*$ as in our main analysis, versus when it ranks organic results independently of sellers' bids by setting $T = 0$, with the value of ϕ assumed exogenous in both cases. We first present the results in Proposition 5 and Figure 10.

Proposition 5 (Comparison with Independent Listing Under Exogenous Commission Rate). *Given a fixed commission rate ϕ, if ϕ is small (i.e., $\phi < 1 - \frac{u_0}{u_0^M}$), strategic listing leads to higher commission revenue and advertising revenue for the platform relative to independent listing. If ϕ is intermediate (i.e., $1 - \frac{u_0}{u_0^M} < \phi < 1 - \frac{u_0}{u_0^H}$), strategic listing leads to lower commission revenue and advertising revenue for the platform. If ϕ is large enough, both listing strategies lead to zero revenue. Overall, under exogenous commission rate, strategic listing is beneficial for the platform when the commission rate is small and it can be harmful when the commission rate is intermediate.*

From Figure 10(a), we observe that when ϕ is exogenously given, strategic listing (represented by solid lines) may not necessarily benefit the platform, compared with independent listing (represented by dotted lines). Specifically, strategic listing is beneficial whenever sellers' participation is ensured, but it can be harmful if sellers stop participating. Based on Proposition 2, as long as sellers participate (given $\phi < 1 - \frac{u_0}{u_0^M}$), strategic listing improves both the platform's commission revenue and its advertising revenue. However, when ϕ exceeds $1 - \frac{u_0}{u_0^M}$ and is below $1 - \frac{u_0}{u_0^H}$, sellers participate under independent listing but not under strategic listing, and this is the scenario where the platform is better off under independent listing.

The discussion in this section suggests that it is crucial for the platform to adjust the commission rate to obtain the full benefits of strategic listing. In the scenario where the commission rate cannot be adjusted solely based on information weight T, however, the platform may not always benefit from strategic listing. Our results shed light on the discrepancy between e-commerce marketplaces and search engines on their adoption of strategic listing. As mentioned earlier, to make sure that search advertising does not affect its core reputation as a search engine, Google explicitly promises that the listings that appear in search advertising do not affect the rankings or listings of the regular organic Google search results. Our results show that it can indeed be optimal for Google to commit to independent listing when the monetization of its organic activity cannot be directly optimized (corresponding to exogenous commission rate in our framework).

5.2. Correlation Between Platform's Information and Sellers' Information

In the main analysis, we keep the platform's information λ_{ki} and a seller's information q_i independent to simplify the analysis and highlight key insights. In this extension, we allow for a correlation between λ_{ki} and q_i to capture the scenario where there is an overlap in sellers' information and the platform's information. We show that with correlated λ_{ki} and q_i, our insights remain qualitatively the same.

We model the correlation by assuming that λ_{ki} is equal to q_i with a probability of $0 \le \rho \le 1$, and it follows an independent uniform distribution otherwise. Given a random draw of $q_i \sim U[0,1]$, we modify the distribution of λ_{ki} as follows:

$$\lambda_{ki} \begin{cases} = q_i, & \text{w.p. } \rho, \\ \sim U[0,1], & \text{w.p. } 1-\rho. \end{cases}$$

With correlated λ_{ki} and q_i, consumer click strategies stay the same, as stated in Proposition 1 (see Section OA2 in the online appendix for the proof). The intuition is that, compared with the independent case, it is less likely for Scenario (b) to happen (because if λ_{ki} realizes the same as q_i, then it is impossible that $q_1 > q_2$ and $Tq_1 + (1-T)\lambda_{k1} < Tq_2 + (1-T)\lambda_{k2}$ can be satisfied at the same time). However, conditional on Scenario (b) happening (when λ_{ki} is independent of q_i), consumers' expected match probabilities with the two sellers remain the same.

Next we derive the platform's two streams of revenues. First, consider the scenario where the correlation between q_i and λ_{ki} is close to one, that is, $\rho \to 1$. Then, if a seller loses the ad slot, it will be almost impossible for him to show up in the organic slot, as a lower q_i also implies a lower λ_{ki}. Consequently, a seller bids truthfully at $(1-\phi)\, q_i$, as in a standard single-slot second-price auction. In this extreme scenario, the expected demand is $\int_0^1 \mathbb{E}_{q_i,q_j}[q_i|q_i > q_j]\, d\theta_k = \frac{2}{3}$, and the expected advertising revenue for the platform is $2\int_0^1\int_0^{q_j} (1-\phi)\, q_i\, dq_i\, dq_j = (1-\phi)\frac{1}{3}$.

More generally, given $0 \le \rho \le 1$, a seller's bid, the expected demand generated, the platform's revenue, and the seller's net profit are all weighted averages of the respective quantities in the main analysis with a probability of $1-\rho$ and those in the perfectly correlated case with a probability of ρ (see Section OA2 in the online appendix for details). Therefore, they all exhibit the same comparative statics against T as in the main analysis. The intuition is that when the platform has the same information as the seller (with a probability of ρ), none of the previous variables in our interest are affected by T, as a seller's bid does not influence his organic ranking. When the platform's information and the seller's information are correlated, the optimal marketplace design is as given by Proposition 6.

Proposition 6 (Correlated Information). *When the seller's information q_i and the platform's information λ_{ki} are correlated, if sellers' outside option is small ($u_0 \le (1-\rho)u_0^M + \rho\frac{1}{6}$), the optimal information weight is $T^* = T^{Sales}$; furthermore, the optimal commission rate ϕ^* decreases as sellers' outside option increases. When the sellers' outside option is intermediate ($(1-\rho)u_0^M + \rho\frac{1}{6} < u_0 \le (1-\rho)u_0^H + \rho\frac{1}{6}$), the optimal information weight T^* decreases from T^{Sales} to zero as sellers' outside option increases; furthermore, the optimal commission rate is $\phi^* = 0$. When the sellers' outside option is large enough ($u_0 > (1-\rho)u_0^H + \rho\frac{1}{6}$), sellers do not participate under any choice of information weight and commission rate.*

Comparing Propositions 3 and 6, we see that our insights in the main analysis remain qualitatively the same even with correlated λ_{ki} and q_i. However, as the platform's information becomes more correlated with the sellers' information, the gain for the platform to adopt strategic listing relative to independent listing reduces. This is as expected, and in the extreme case with $\rho \to 1$, the gain becomes zero. Essentially, the platform benefits from strategic listing when eliciting seller private information about demand matters.

6. Conclusions and Discussion

Virtually nonexistent two decades ago, e-commerce platforms, such as Amazon and Alibaba, now account for large shares of online sales worldwide. In addition, advertising on e-commerce platforms is an increasingly pervasive and economically important phenomenon. In this paper, we find that advertising is more than just a revenue driver for e-commerce platforms; in fact, it plays an important informational role by enabling the platform to learn sellers' private information. This improves the set of results presented to consumers; that is, the platform's practice of strategic listing has an information effect that helps the platform to improve its organic results, thus increasing revenue through sales commissions. However, because outcomes of the ad auction influence the organic placements, an externality is introduced, and competition in the ad auction generally increases, leading to a competition effect. This leads to a lower incentive for sellers to participate on the platform, and to ensure seller participation, the platform must in turn set the sales commission rate appropriately. Overall, we find that as it becomes more difficult to incentivize sellers' participation (because of, say, a better outside option), the platform should reduce both the dependence of the organic results on the information learned from sponsored ad bidding and its commission rate, which may even be zero. The net effect is that the platform relies more on advertising revenue and less on sales commissions.

Our results show that e-commerce platforms may benefit significantly from strategic listing. Such a strategy may have been employed in the industry—for example, on Amazon, higher ranking in sponsored results tends to correlate with higher organic ranking. Our analysis also sheds light on variation in strategies across different retail platforms. For instance, our model shows that the sales commission rate charged by a platform may change with how easy it is to get sellers on to the platform. The sales commission rate may even be zero, in which case the platform depends purely on advertising for its revenue. Indeed, Alibaba relies primarily on advertising revenue while charging a minimal commission rate for each transaction (0%–5%). Strategic listing also helps to address the cold start problem at marketplaces, which arises when the platform has little information about new sellers or products and therefore finds it difficult to recommend new products, by exploiting information revealed from sellers' bids for sponsored listings. Furthermore, we find that if the monetization rate of the organic side is not easily tuned, then strategic listing might hurt the platform compared with independent listing. For instance, whereas Amazon can choose its commission rate for sales from organic (and sponsored) results, Google cannot as easily choose or modify the long-term benefit from its organic results and essentially must treat this as exogenous. We find that, in line with this, Google's declared commitment to not using information from ad auctions to influence the organic results might be optimal.

In formulating our model, we have made a number of assumptions. For instance, we consider only ad auctions with one advertising slot. Our main findings carry through qualitatively if we consider ad auctions with multiple slots as the same set of forces is at play. However, there may be other assumptions that could be revisited. For instance, in some industry sectors, there are multiple similar competing platforms, all of which allow advertising by third-party sellers (e.g., Zomato and Swiggy for food delivery in India). This can influence the seller's incentives to participate on one or both platforms, and because the participation constraint plays an important role in our analysis, this direction of research is promising. Finally, we refrain from price competition by modeling the consumer consumption utility in a simplified manner. Further research is needed to accommodate price competition to fully understand consumer welfare and regulatory implications.

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Appendix

A.1. Solution for Consumer Choice

To facilitate the analysis, we first define several function operators. Given T and q_1, define $\hat{E}^{AO}(\cdot)$ as the expectation of $(\cdot)$ over the parameter space of $\lambda_{k1}, q_2, \lambda_{k2}$ satisfying $q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} > Tq_2 + (1-T)\lambda_{k2}$, so that seller 1 wins both the ad slot and the organic slot (represented by "AO"). Similarly, define $\hat{E}^{A}(\cdot)$ as the expectation of $(\cdot)$ in the parameter space of $\lambda_{k1}, q_2, \lambda_{k2}$ satisfying $q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} < Tq_2 + (1-T)\lambda_{k2}$, so that the seller only wins the ad slot (represented by "A"). Define $\hat{E}^{O}(\cdot)$ as the expectation of $(\cdot)$ in the parameter space of $\lambda_{k1}, q_2, \lambda_{k2}$ satisfying $q_1 < q_2, Tq_1 + (1-T)\lambda_{k1} > Tq_2 + (1-T)\lambda_{k2}$, so that the seller only wins the organic slot (represented by "O"). The results are given below (see the online appendix, Section OA1.1, for more details):

$$\hat{E}^{AO}_{\lambda_{k1},q_2,\lambda_{k2}}(\cdot) = \mathbb{E}_{\lambda_{k1},q_2,\lambda_{k2}}\left[(\cdot)\,\mathbb{1}_{\{q_1>q_2,\,Tq_1+(1-T)\lambda_{k1}>Tq_2+(1-T)\lambda_{k2}\}}\right],$$
$$= \begin{cases} \int_0^1 \int_0^{\lambda_{k1}} \int_0^{q_1} (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1} \\ \quad + \int_0^{1-\frac{T}{1-T}q_1} \int_{\lambda_{k1}}^{\lambda_{k1}+\frac{T}{1-T}q_1} \int_0^{q_1-\frac{1-T}{T}(\lambda_{k2}-\lambda_{k1})} \\ \quad (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1} \\ \quad + \int_{1-\frac{T}{1-T}q_1}^{1} \int_{\lambda_{k1}}^{1} \int_0^{q_1-\frac{1-T}{T}(\lambda_{k2}-\lambda_{k1})} \\ \quad (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1}, & 0 < T \le \dfrac{1}{1+q_1}, \\ \int_0^1 \int_0^{\lambda_{k1}} \int_0^{q_1} dq_2\, d\lambda_{k2}\, d\lambda_{k1} \\ \quad + \int_0^1 \int_{\lambda_{k1}}^1 \int_0^{q_1-\frac{1-T}{T}(\lambda_{k2}-\lambda_{k1})} (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1}, & T > \dfrac{1}{1+q_1}. \end{cases} \tag{A.1}$$

$$\hat{E}^{A}_{\lambda_{k1},q_2,\lambda_{k2}}(\cdot) = \mathbb{E}_{\lambda_{k1},q_2,\lambda_{k2}}\left[(\cdot)\,\mathbb{1}_{\{q_1>q_2,\,Tq_1+(1-T)\lambda_{k1}<Tq_2+(1-T)\lambda_{k2}\}}\right],$$
$$= \begin{cases} \int_0^{1-\frac{T}{1-T}q_1} \int_{\lambda_{k1}}^{\lambda_{k1}+\frac{T}{1-T}q_1} \int_{q_1-\frac{1-T}{T}(\lambda_{k2}-\lambda_{k1})}^{q_1} \\ (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1} \\ + \int_{1-\frac{T}{1-T}q_1}^{1} \int_{\lambda_{k1}}^{1} \int_{q_1-\frac{1-T}{T}(\lambda_{k2}-\lambda_{k1})}^{q_1} \\ (\cdot)\, dq_2\, d\lambda_{k2}\, d\lambda_{k1} \\ + \int_0^{1-\frac{T}{1-T}q_1} \int_{\lambda_{k1}+\frac{T}{1-T}q_1}^{1} \int_0^{q_1} (\cdot)\, dq_2\, d\lambda_{k2}\, d\lambda_{k1}, & 0 < T \le \dfrac{1}{1+q_1}, \\ \int_0^1 \int_{\lambda_{k1}}^1 \int_{q_1-\frac{1-T}{T}(\lambda_{k2}-\lambda_{k1})}^{q_1} (\cdot)\, dq_2\, d\lambda_{k2}\, d\lambda_{k1}, & T > \dfrac{1}{1+q_1}. \end{cases} \tag{A.2}$$

$$\hat{E}^{O}_{\lambda_{k1},q_2,\lambda_{k2}}(\cdot) = \mathbb{E}_{\lambda_{k1},q_2,\lambda_{k2}}\left[(\cdot)\,\mathbb{1}_{\{q_1<q_2,\,Tq_1+(1-T)\lambda_{k1}>Tq_2+(1-T)\lambda_{k2}\}}\right],$$
$$= \begin{cases} \int_{\frac{T}{1-T}(1-q_1)}^{1} \int_0^{\lambda_{k1}-\frac{T}{1-T}(1-q_1)} \int_{q_1}^{1} \\ (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1} \\ + \int_{\frac{T}{1-T}(1-q_1)}^{1} \int_{\lambda_{k1}-\frac{T}{1-T}(1-q_1)}^{\lambda_{k1}} \int_{q_1}^{q_1+\frac{1-T}{T}(\lambda_{k1}-\lambda_{k2})} \\ (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1} \\ + \int_0^{\frac{T}{1-T}(1-q_1)} \int_0^{\lambda_{k1}} \int_{q_1}^{q_1+\frac{1-T}{T}(\lambda_{k1}-\lambda_{k2})} \\ (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1}, & 0 < T \le \dfrac{1}{2-q_1}, \\ \int_0^1 \int_0^{\lambda_{k1}} \int_{q_1}^{q_1+\frac{1-T}{T}(\lambda_{k1}-\lambda_{k2})} \\ (\cdot)\; dq_2\, d\lambda_{k2}\, d\lambda_{k1}, & T > \dfrac{1}{2-q_1}. \end{cases} \tag{A.3}$$

Now we are ready to derive a consumer's expected match probability with both sellers.

A.1.1. Scenario (a)

In this scenario, seller 1 occupies both the sponsored slot and the organic slot. Given this, consumers infer that $q_1 > q_2$ (under the belief that the seller who bids higher is the higher-quality seller) and that $Tq_1 + (1-T)\lambda_{k1} > Tq_2 + (1-T)\lambda_{k2}$ (from the fact that seller 1 obtains the organic slot). Given the two conditions, consumers update seller 1's expected match probability as

$$\begin{aligned}
&\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1} \mid q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} > Tq_2 + (1-T)\lambda_{k2}],\\
&= \frac{\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1}\ \mathbb{1}_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k1}>Tq_2+(1-T)\lambda_{k2}\}}]}{P(q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} > Tq_2 + (1-T)\lambda_{k2})},\\
&= \frac{\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1}\ \mathbb{1}_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k1}>Tq_2+(1-T)\lambda_{k2}\}}]}{\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\mathbb{1}_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k1}>Tq_2+(1-T)\lambda_{k2}\}}]}.
\end{aligned} \tag{A.4}$$

Next, we derive the numerator and denominator in Equation (A.4), respectively. We first evaluate the numerator:

$$\begin{aligned}
&\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1}\ 1_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k1}>Tq_2+(1-T)\lambda_{k2}\}}],\\
&= \mathbb{E}_{q_1}[\hat{E}^{AO}_{\lambda_{k1},q_2,\lambda_{k2}}(\theta_k q_1 + (1-\theta_k)\lambda_{k1})],\\
&= \mathbb{E}_{q_1}\begin{cases} \frac{1}{6}q_1(\theta_k(3q_1-2)+2) + f_1(q_1), & 0 < T \le \frac{1}{1+q_1},\\ \frac{1}{6}q_1(\theta_k(3q_1-2)+2) \\ \quad + \frac{\theta_k + T\left(-\theta_k + 12\theta_k q_1^2 + 4q_1 + 1\right) - 4\theta_k q_1 - 1}{24T}, & T > \frac{1}{1+q_1},\end{cases}
\end{aligned} \tag{A.5}$$

$$= \begin{cases} \frac{(4-3\theta_k)T^3 + (9\theta_k - 35)T^2 - 5(\theta_k - 10)T - 20}{120(T-1)^3}, & 0 < T \le \frac{1}{2},\\ \frac{\theta_k + (13\theta_k + 36)T^3 - 7T^2 - 4\theta_k T + T}{120T^3}, & T > \frac{1}{2},\end{cases} \tag{A.6}$$

where $f_1(q_1) = -\frac{q_1^2 T(T^2(-6\theta_k + (3\theta_k+1)q_1^2 + (8\theta_k+4)q_1 + 6) - 4T(-3\theta_k + \theta_k q_1^2 + 5\theta_k q_1 + q_1 + 3) + 6\theta_k(2q_1 - 1) + 6)}{24(T-1)^3}$ in Equation (A.5). In arriving at Equation (A.5), we directly apply $\hat{E}^{AO}$ (given in Equation (A.1)) to $\theta_k q_1 + (1-\theta_k)\lambda_{k1}$. Equation (A.6) gives the final result by further integrating over q_1.

The denominator in Equation (A.4) can be calculated following the same logic by applying $\hat{E}^{AO}$ to an indicator function. This results in $\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\mathbb{1}_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k1}>Tq_2+(1-T)\lambda_{k2}\}}] = \mathbb{E}_{q_1}[\hat{E}^{AO}_{\lambda_{k1},q_2,\lambda_{k2}}(\mathbb{1})]$, which is equal to $\frac{T^2-8T+6}{24(T-1)^2}$ if $0 < T \le \frac{1}{2}$, and $\frac{17T^2-6T+1}{24T^2}$ if $\frac{1}{2} < T \le 1$. Dividing (A.6) by the previous result, a consumer's conditional match probability with seller 1 in this scenario is

$$\begin{aligned}
&\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1} \mid q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} > Tq_2 + (1-T)\lambda_{k2}],\\
&= \begin{cases} \frac{-20 + T^3(4-3\theta_k) - 5T(-10+\theta_k) + T^2(-35+9\theta_k)}{5(-1+T)(6-8T+T^2)}, & 0 < T \le \frac{1}{2},\\ \frac{T - 7T^2 + 36T^3 + \theta_k - 4T\theta_k + 13T^3\theta_k}{5T - 30T^2 + 85T^3}, & \frac{1}{2} < T \le 1.\end{cases}
\end{aligned}$$

A consumer's conditional expected match probability with seller 2 can be obtained by applying the same operator $E^{\hat{AO}}$ to $\theta_k q_2 + (1-\theta_k)\lambda_{k2}$. The online appendix, Section OA1.1, shows that a consumer's expected match utility with seller 2 in this scenario is

$$\begin{aligned}
&\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k2} \mid q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} > Tq_2 + (1-T)\lambda_{k2}],\\
&= \begin{cases} \frac{-10 + 5T(4+\theta_k) + T^3(1+3\theta_k) - T^2(10+9\theta_k)}{5(-1+T)(6-8T+T^2)}, & 0 < T \le \frac{1}{2},\\ \frac{-23T^2 + T^3(49-13\theta_k) - \theta_k + 4T(1+\theta_k)}{5T - 30T^2 + 85T^3}, & \frac{1}{2} < T \le 1.\end{cases}
\end{aligned}$$

Comparing the previous two expressions, we find that consumers always expect a higher match probability with seller 1 than with seller 2 in Scenario (a). Therefore, all consumers click on seller 1, even if seller 2 is shown in the second organic slot.

A.1.2. Scenario (b)

This scenario can be solved using a logic similar to that for Scenario (a). To avoid repetition, we leave the details to online appendix, Section OA1.1, and summarize the results below. First, we derive $\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1} \mid q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} < Tq_2 + (1-T)\lambda_{k2}]$ in a similar way as Scenario (a). The only difference is that we apply operator $\hat{E}^{A}$ instead of $\hat{E}^{AO}$ to $m_{k1} = \theta_k q_1 + (1-\theta_k)\lambda_{k1}$ when seller 1 only wins the ad slot in this case:

$$\begin{aligned}
&\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1}\ \mathbb{1}_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k1}<Tq_2+(1-T)\lambda_{k2}\}}],\\
&= \mathbb{E}_{q_1}[\hat{E}^{A}_{\lambda_{k1},q_2,\lambda_{k2}}(\theta_k q_1 + (1-\theta_k)\lambda_{k1})],\\
&= \begin{cases} \frac{-10(\theta_k+1) + 13(\theta_k+2)T^3 - (39\theta_k+55)T^2 + 5(7\theta_k+8)T}{120(T-1)^3}, & 0 < T \le \frac{1}{2},\\ -\frac{\theta_k + 3(\theta_k+2)T^3 - 7T^2 - 4\theta_k T + T}{120T^3}, & T > \frac{1}{2}.\end{cases}
\end{aligned} \tag{A.7}$$

Next, the probability of Scenario (b) happening, $P(q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} < Tq_2 + (1-T)\lambda_{k2})$, is $\frac{11T^2-16T+6}{24(T-1)^2}$ if $0 < T \le \frac{1}{2}$, and it is $\frac{-5T^2+6T-1}{24T^2}$ if $\frac{1}{2} < T \le 1$. Given these, a consumer's expected match probability with seller 1 is

$$\begin{aligned}
&\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1} \mid q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} < Tq_2 + (1-T)\lambda_{k2}],\\
&= \begin{cases} \frac{-10(\theta_k+1) + 13(\theta_k+2)T^3 - (39\theta_k+55)T^2 + 5(7\theta_k+8)T}{5(T-1)(11T^2-16T+6)}, & 0 < T \le \frac{1}{2},\\ \frac{\theta_k - 3(\theta_k+2)T^2 - 3\theta_k T + T}{5(1-5T)T}, & \frac{1}{2} < T \le 1.\end{cases}
\end{aligned}$$

A consumer's expected utility with seller 2, $\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k2}\ \mathbb{1}_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k2}<Tq_1+(1-T)\lambda_{k2}\}}]$, is equivalent to $\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k1}\ \mathbb{1}_{\{q_1<q_2, Tq_1+(1-T)\lambda_{k2}>Tq_1+(1-T)\lambda_{k2}\}}]$. The latter can be solved by applying $\hat{E}^{O}$ (given by Equation (A.3)) to m_{k1}. This results in

$$\begin{aligned}
&\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k2}\ \mathbb{1}_{\{q_1>q_2, Tq_1+(1-T)\lambda_{k2}<Tq_1+(1-T)\lambda_{k2}\}}],\\
&= \mathbb{E}_{q_1}[\hat{E}^{O}_{\lambda_{k1},q_2,\lambda_{k2}}(\theta_k q_1 + (1-\theta_k)\lambda_{k1})],\\
&= \begin{cases} \frac{10(\theta_k-2) + (29-13\theta_k)T^3 + (39\theta_k-80)T^2 - 35(\theta_k-2)T}{120(T-1)^3}, & 0 < T \le \frac{1}{2},\\ \frac{(T-1)\left(-\theta_k + (3\theta_k-19)T^2 + (3\theta_k+4)T\right)}{120T^3}, & T > \frac{1}{2}.\end{cases}
\end{aligned} \tag{A.8}$$

Dividing Equation (A.8) by the probability of Scenario (b) happening, we find that if clicking on the seller in the first organic slot, consumers expect a utility of

$$\mathbb{E}_{q_1,\lambda_{k1},q_2,\lambda_{k2}}[\, m_{k2} \mid q_1 > q_2, Tq_1 + (1-T)\lambda_{k1} < Tq_2 + (1-T)\lambda_{k2}],$$
$$= \begin{cases} \dfrac{T^3(29-13\theta_k)+10(-2+\theta_k) \\ -35T(-2+\theta_k)+T^2(-80+39\theta_k)}{5(-1+T)(6-16T+11T^2)}, & 0 < T \le \dfrac{1}{2}, \\ \dfrac{T^2(19-3\theta_k)+\theta_k - T(4+3\theta_k)}{5(1-5T)T}, & \dfrac{1}{2} < T \le 1. \end{cases}$$

Comparing a consumer's match probabilities for seller 1 and seller 2, we obtain that the match probability is higher by clicking seller 1 (in the ad slot) than seller 2 (in the organic slot) if and only if $\theta_k > \theta^T$, where θ^T is given in the main analysis.

Notice that in the special case of $T = 0$, we have $\theta^T = \frac{1}{2}$. Intuitively, when the organic placement is independent of sellers' advertising bids, the ad slot presents the higher-quality seller, whereas the organic slot presents the seller with a better personal fit. Consequently, consumers click on the ad slot if and only if they favor product quality more than personal fit (i.e., $\theta_k < \frac{1}{2}$).

A.2. Solution for Sellers' Bidding Strategy

To derive the equilibrium bid, we can directly apply $\hat{E}^{AO}$, $\hat{E}^{A}$, and $\hat{E}^{O}$ as defined in Section A.1 to simplify the calculation. We first evaluate the partial derivative of $U_{q_i}(q_i{}')$ against $q_i{}'$,

$$\frac{\partial U_{q_i}(q_i{}')}{\partial q_i{}'}$$
$$= \frac{\partial\left(\int_0^{q_i{}'} \mathbb{E}_{\lambda_{ki},\lambda_{kj},\theta_k}[(1-\phi)\, m_{ki}\, 1_{\{Tq_i{}'+(1-T)\lambda_{ki} > Tq_j+(1-T)\lambda_{kj}\}}]dq_j\right)}{\partial q_i{}'}$$
$$+ \frac{\partial\left(\int_0^{q_i{}'} \mathbb{E}_{\lambda_{ki},\lambda_{kj},\theta_k}[(1-\phi)\, m_{ki}\, 1_{\{Tq_i{}'+(1-T)\lambda_{ki} < Tq_j+(1-T)\lambda_{kj},\theta_k>\theta^T\}}]dq_j\right)}{\partial q_i{}'}$$
$$+ \frac{\partial\left(\int_{q_i{}'}^{1} \mathbb{E}_{\lambda_{ki},\lambda_{kj},\theta_k}[(1-\phi)\, m_{ki}\, 1_{\{Tq_i{}'+(1-T)\lambda_{ki} > Tq_j+(1-T)\lambda_{kj},\theta_k<\theta^T\}}]dq_j\right)}{\partial q_i{}'}$$
$$-b(q_i{}').$$

Without loss of generality, we use $i = 1$ and $j = 2$. The first term in the previous expression is equal to

$$\frac{\partial}{\partial q_1{}'}\int_0^{q_1{}'} \mathbb{E}_{\lambda_{k1},\lambda_{k2},\theta_k}[(1-\phi)\, m_{k1}\, \mathbb{1}_{\{Tq_1{}'+(1-T)\lambda_{k1} > Tq_2+(1-T)\lambda_{k2}\}}]dq_2,$$
$$= (1-\phi)\frac{\partial}{\partial q_1{}'}\mathbb{E}_{\theta_k}[\hat{E}^{AO}_{\lambda_{k1},q_2,\lambda_{k2}}(m_{k1})\,],$$
$$= (1-\phi)\begin{cases} -\dfrac{3q_1(T-1) \\ ((q_1{}'^2+2q_1{}'-\mathbb{1}) \\ T^2-2(q_1{}'-1)T-1) \\ -3(q_1{}'^2+2q_1{}'-2)T^2 \\ +(q_1{}'^3+3q_1{}'^2+3q_1{}'-2) \\ T^3+3(q_1{}'-2)T+2}{12(T-1)^3}, & T \le \dfrac{1}{1+q_1{}'}, \\ \dfrac{1}{4}(2q_1+1), & T > \dfrac{1}{1+q_1{}'}. \end{cases}$$

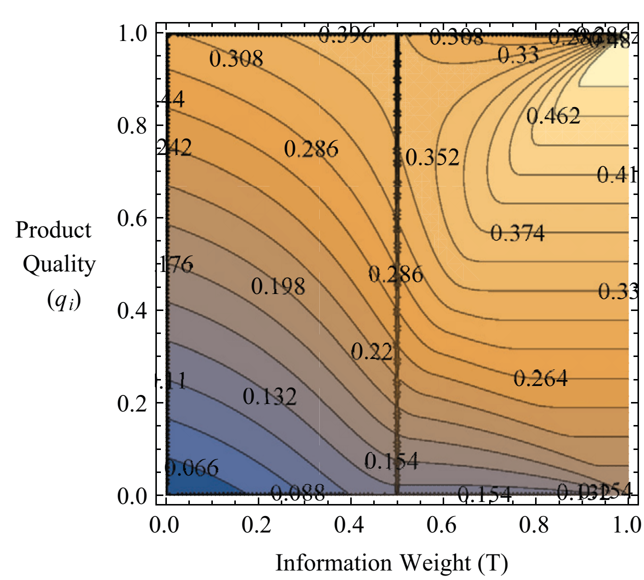
The second term and the third term in the previous expression can be obtained following a similar logic. Combined together, we obtain $\frac{\partial U_{q_1}(q_1{}')}{\partial q_1{}'}$ (see the online appendix, Section OA1.2, for details). From $\frac{\partial U_{q_1}(q_1{}')}{\partial q_1{}'}|_{q_1{}'=q_1} = 0$, we can obtain the analytical solution for $b(q_1)$,

$$b(q_1) = \begin{cases} -\dfrac{(7T-2)(q_1T+T-1)^2(-7T^2+9T+q_1 \\ (50T^2+11T-6)-2)}{48(T-1)(3T^2+3T-1)^2}, & \dfrac{1}{2} < T \le \dfrac{1}{q_1+1}, \\ \dfrac{(q_1T+T-1)^2(23T^2-30T+10) \\ (23T^3-53T^2+40T+q_1 \\ (110T^3-339T^2+310T-90)-10)}{48(T-1)(-13T^3+39T^2-35T+10)^2}, & 0 < T < \dfrac{1}{2}, \end{cases}$$
$$+\begin{cases} \dfrac{T(13T-3)((q_1-2)T+1)^2((1-38q_1)T^3+ \\ (33q_1-17)T^2+(34-5q_1)T-8)}{48(T-1)^3(3T^2+3T-1)^2}, & \dfrac{1}{2} < T < \dfrac{1}{2-q_1}, \\ f_5(q_1), & 0 < T < \dfrac{1}{2}, \end{cases}$$
$$+\begin{cases} \dfrac{1}{4}(2q_1+1), & T > \dfrac{1}{1+q_1}, \\ \dfrac{(3-4T)T^2q_1^3-3T(3T^2-5T+2)q_1^2 \\ -3(T-1)^2q_1+2(T-1)^3}{12(T-1)^3}, & T \le \dfrac{1}{1+q_1}. \end{cases} \tag{A.9}$$

where $f_5(q_1) \equiv -\dfrac{((q_1-2)T+1)^2 \\ (3T^3-25T^2+30T-10)((q_1T+T-2) \\ (49T^3-131T^2+110T-30)+3q_1 \\ (3T^4-28T^3+55T^2-40T+10))}{48(T-1)^3(-13T^3+39T^2-35T+10)^2}$. Replacing q_1 with q_i in the previous expression gives $b(q_i)$.

Because of the complexity of the analytical solution, we use Figure A.1 to illustrate a seller's bid as a function of the platform's information weight T and the seller's quality q_i. Based on the contour plot in Figure A.1, we observe that sellers' bid $b(q_i)$ indeed increases in q_i under $T \le \bar{T}$, where $\bar{T} = 0.5$ given $\theta_k \sim U[0,1]$. When $T > \bar{T}$, however, there does not exist a pure strategy bidding equilibrium. Although this

Figure A.1. (Color online) Sellers' Bidding Strategy $b(q_i)$



Note. $\phi = 0.3$ in the figure.

contradicts with our initial assumption in solving the equilibrium bid, below we show that if the platform wants to maximize its profit, it is suboptimal for it to choose a T larger than $\bar{T}$. The outline of the argument is that the total system surplus for $T=\bar{T}$ is larger than the total system surplus for $\bar{T}<T\le 1$, and the platform obtains all of the system surplus for $T=\bar{T}$ as its profit. Therefore, even if the platform were to obtain the total system surplus for $\bar{T}<T\le 1$ as its profit, this profit would still be less than the profit at $T=\bar{T}$. This implies that, for the purpose of profit maximization, considering $T\le \bar{T}$ is sufficient. The detailed argument follows.

First, given a fixed T, the total surplus generated from the transaction under a mixed strategy equilibrium will be lower than that under a pure strategy equilibrium even if q_1 and q_2 can be perfectly inferred by the platform. This is because under a mixed strategy bidding equilibrium, it is possible for the lower-quality seller to win the ad slot, which results in information loss (compared with a pure strategy equilibrium where q_1 and q_2 are perfectly inferred) and leads to less consumer demand. Therefore, for a fixed T, the marketplace generates the maximal possible expected surplus when there exists a pure bidding equilibrium and q_1 and q_2 can be perfectly inferred. We can show that this maximal possible total surplus first increases then decreases with T and is maximized at $T^{Sales}=0.3$. Therefore, the total possible surplus generated under $\bar{T}<T\le 1$ is lower than that at $T=\bar{T}$, because $\bar{T}=0.5$ exceeds the value of $T^{Sales}=0.3$.

Furthermore, as shown in Section 4.3.2, for $0\le T\le \bar{T}$ where a pure equilibrium exists, with an optimally chosen commission rate, the platform can extract all surplus beyond a seller's outside option. Therefore, for $T=\bar{T}$, the platform's equilibrium profit is equal to the total possible surplus generated, whereas for $\bar{T}<T\le 1$, the platform obtains less than the total possible surplus generated (because of the mixed strategy bidding equilibrium). Because the total possible surplus generated for $\bar{T}<T\le 1$ is lower than for $T=\bar{T}$, the platform always makes less profit for $\bar{T}<T\le 1$ than for $T=\bar{T}$.

A.3. Solution for Platform's Commission Revenue and Advertising Revenue

In this section, we first derive the platform's commission revenue. We then find the platform's advertising revenue.

A.3.1. Platform's Commission Revenue

To evaluate the platform's commission revenue, we first derive, given T and θ_k, the probability that the consumer finds a match $d(T,\theta_k)$. Based on Proposition 1, we have

$$\begin{aligned}d(T,\theta_k) &= 2\mathbb{E}_{q_i,\lambda_{ki},q_j,\lambda_{kj}}[m_{ki}\mathbb{1}_{\{q_i>q_j,Tq_i+(1-T)\lambda_{ki}>Tq_j+(1-T)\lambda_{kj}\}}]\\ &\quad+2\mathbb{E}_{q_i,\lambda_{ki},q_j,\lambda_{kj}}[m_{ki}\mathbb{1}_{\{q_i>q_j,Tq_i+(1-T)\lambda_{ki}<Tq_j+(1-T)\lambda_{kj},\theta_k>\theta^T\}}]\\ &\quad+2\mathbb{E}_{q_i,\lambda_{ki},q_j,\lambda_{kj}}[m_{ki}\mathbb{1}_{\{q_i<q_j,Tq_i+(1-T)\lambda_{ki}>Tq_j+(1-T)\lambda_{kj},\theta_k<\theta^T\}}],\\ &=\begin{cases}2\text{ A.6}+2\text{ A.8}, & 0<T\le\frac{1}{2},\\ 2\text{ A.6}+2\text{ A.7}, & \frac{1}{2}<T\le 1.\end{cases}\end{aligned}$$

where the required quantities are as defined in (A.6), (A.7), and (A.8), and 1 stands for the indicator function. In the previous equation, the first term stands for Scenario (a), where the same seller shows up in the ad slot and the organic slot. The rest of the two terms stand for Scenario (b), where the consumer examines the seller in the ad slot if $\theta_k\ge\theta^T$, and the seller in the organic slot if $\theta_k<\theta^T$. Given commission rate ϕ and denoting the expected demand generated by $D(T)$, the platform's commission revenue is given by $\phi D(T)$, expressed as

$$\begin{aligned}\phi D(T) &= \phi\int_0^1 d(T,\theta_k)\,d\theta_k,\\ &=2\phi\begin{cases}\dfrac{1500-9700+25760T^2-35860T^3+27545T^4-11070T^5+1829T^6}{480(-1+T)^3(-10+35T-39T^2+13T^3)}, & 0<T\le\frac{1}{2},\\ \dfrac{9-227T+667T^2+251T^3}{480T(-1+3T+3T^2)}, & \frac{1}{2}<T\le 1.\end{cases}\end{aligned}\tag{A.10}$$

A.3.2. Platform's Advertising Revenue Under Pay-per-Impression

In terms of the advertising revenue, notice that under a second-price auction, the winning seller j pays an advertising price equal to seller i's bid. The expected ad payment under Nash equilibrium can be obtained by taking integrals over $b(q_1)$ as derived in Section A.2. Because of the complexity of the bid function, we compute the integral with the aid of Mathematica:

$$\begin{aligned}&\mathbb{E}_{q_2}[\mathbb{E}_{q_1}[b(q_1)1_{\{q_1<q_2\}}]]+\mathbb{E}_{q_2}[\mathbb{E}_{q_1}[b(q_2)\mathbb{1}_{\{q_1>q_2\}}]],\\ &=2\int_0^1\int_0^{q_2}b(q_1)\,dq_1\,dq_2,\\ &=2(1-\phi)\\ &\quad\begin{cases}\dfrac{-592T^4+10483T^3-5697T^2+813T-7}{960(3T^2+3T-1)^2}, & T>\frac{1}{2},\\ \dfrac{C}{960(T-1)^3(13T^3-39T^2+35T-10)^2}, & T\le\frac{1}{2}.\end{cases}\end{aligned}\tag{A.11}$$

In the previous expression, $C\equiv 24272T^9-173245T^8+559270T^7-1094215T^6+1444080T^5-1328050T^4+840000T^3-347100T^2+84000T-9000$. We can observe that $1-\phi$ appears as a multiplier in the platform's ad revenue. Intuitively, a seller's bid is in proportion to its revenue margin $1-\phi$, where ϕ is the platform's commission rate.

Endnotes

[1] We use "platform" and "marketplace" interchangeably throughout this paper.

[2] See https://www.investopedia.com/articles/investing/121714/how-does-alibaba-make-money-simple-guide.asp.

[3] See https://content26.com/wp-content/uploads/E-Book_The-Definitive-Guide-to-Amazon-Advertising.pdf.

[4] See https://support.google.com/merchants/answer/7679273.

[5] We refer to the sellers as "he" and to the consumers as "she," and use "marketplace" and "platform" interchangeably.

[6] In an extension in Section 5.2, we provide a rigorous analysis by allowing for sellers and platforms to have access to the same type of information, and we show that our insights hold qualitatively.

[7] We provide an example to understand λ_{ki} in this footnote. Denote by α_k the vector of consumer k's preferences (e.g., preferences for different colors), where α_k is the platform's private information. Denote by x_i the covariates of product i (e.g., color of a product), where x_i is common information to seller i and the platform. The

horizontal match component λ_{ki} is given by $\lambda_{ki} = x_i \cdot \alpha_k$, and it is the platform's private information because only the platform knows α_k.

[8] Note that the role of the uncertainty in consumer sensitivity, θ_k, is partly instrumental in rationalizing consumer click behaviors. Our insights would also apply if we apply the same value of θ_k to all consumers and exogenously assume that a fixed fraction of consumers click on the ad slot.

[9] In the most general case, the organic results can be ranked based on $T_1\tilde{q}_i + T_2\lambda_{ki}$, which can be normalized to $T = \frac{T_1}{T_1+T_2}$ as in our model.

[10] Because we assume a search cost of zero for the first search and there is no second search, there is no holdup problem. An alternative formulation can be that the firm sets and commits to prices early. In that case, our results will hold qualitatively if we allow consumers to click on multiple products by incurring a positive search cost for each click, assuming that sellers' prices are low enough for consumers to engage in the search. In particular, our model formulation is equivalent to assuming that the search cost s for examining each product lies in an intermediate range so that consumers will examine exactly one product in equilibrium. Specifically, the search cost should be high enough so that consumers will examine at most one product, that is, $s > \max\{\mathbb{E}[m_{kj} - p_j | q_i > q_j, Tq_i + (1-T)\lambda_{ki} > Tq_j + (1-T)\lambda_{kj}],\ \mathbb{E}[\min\{m_{ki} - p_i, m_{kj} - p_j\} | q_i > q_j, Tq_i + (1-T)\lambda_{ki} < Tq_j + (1-T)\lambda_{kj}]\}$. The search cost also needs to be low enough so that consumers will still conduct search, that is, $s < \min\{\mathbb{E}[m_{ki} - p_i | q_i > q_j, Tq_i + (1-T)\lambda_{ki} > Tq_j + (1-T)\lambda_{kj}],\quad \mathbb{E}[\max\{m_{ki} - p_i, m_{kj} - p_j\} | q_i > q_j, Tq_i + (1-T)\lambda_{ki} < Tq_j + (1-T)\lambda_{kj}]\}$. To ensure that the previous parameter space is nonempty, we need p_i and p_j to be low enough so that consumers have an incentive to conduct the search in the first place.

[11] A seller's decision to join the platform is a long-term retail strategy decision, for example, of selling on Amazon or not. In comparison, the product improvements and modifications happen more frequently. Therefore, the decision to join is made before the seller observes (say, from private market research) the perceived consumer utility for a new characteristic introduced in the product that he is selling, that is, observes q_i.

[12] In the model, the winner of the ad slot depends only on sellers' bids, and does not depend on the platform's information about personal fit. Our insights remain robust even if we allow the marketplace to use its own personal fit information to rank advertising results, which is similar to the "quality score" used by search engines in practice to better allocate ad slots (see Section OA3 in the online appendix for more details).

[13] Nevertheless, if we allow T to be decided after the sellers have made their participation decisions and have submitted their bids (which takes care of the commitment issue), we can obtain qualitatively the same implications (see Section OA4 in the online appendix for details).

[14] In this footnote, we provide more intuitions on why there does not exist a pure strategy equilibrium in the bidding game when $T > \bar{T}$. If we assume the bid function increases with q_i, then the bid function solved under this assumption first increases then decreases with q_i given $T > \bar{T}$, thus contradicting the assumption. This is because when T is sufficiently high, θ^T will be so large that very few consumers click on the seller in the ad slot in Scenario (b). Such a negative effect of bidding high can dominate its positive effect of improving organic ranking when both T and q_i are large.

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