Online Retail Platform, Consumer Search, and Filtering

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Abstract

We study how the consumer’s search cost and search-outcome filtering affect consumers’ search behaviors and the pricing strategies and profits of a retail platform and sellers on it. Sellers selling differentiated products compete on prices and the platform charges them per-unit-sale referral fees. We show that although a search-cost decrease intensifies competition between sellers, their profit can increase because more consumers will shop on the platform. A lower search cost always increases the profit of the platform when it optimally adjusts its referral fee. When the search cost decreases, the platform should reduce its fee if demand elasticity increases significantly, leading to an all-win for the platform, sellers and consumers. In other cases where the platform’s optimal referral fee increases, a search-cost decrease can lead to higher equilibrium retail prices. When consumers can filter search outcomes based on some product attributes, they benefit less from searching, search less, but buy products with better match in expectation. We also show that filtering can either intensify or alleviate sellers’ competition, unlike a search-cost decrease always aggravates competition.

Key words: search, retail platform, pricing, e-commerce, competition, filtering, channel
INTRODUCTION

Online retailing is growing rapidly. In the United States, online retail sales as a percent of total retail sales have nearly tripled from 2.7% in 2006 to 7.5% in 2015, and the estimated sales on online retail platforms reached $389 billion in 2016. In a survey covering 19 countries and territories, more than 95% of some 19,000 respondents have online shopping experience, and more than half of them shop online at least once a month (PwC 2015). Consumers often buy products from independent third-party sellers on retail platforms (e.g., Amazon.com, eBay.com, and Taobao.com). Take Amazon.com, which accounts for 43% of United States online retail sales. In 2015, over two million third-party sellers sold products on Amazon.com worldwide, contributing to 83% of revenue on Amazon.com. A platform’s profit typically comes from the referral fees, a.k.a. commissions paid by sellers based on their prices and unit sales. In Q1 2017, Amazon.com received $8 billion from referral fees collected from third-party sellers.

Consumers search for products that match their preferences better or have lower prices. The consumer’s search cost for product information on online retail platforms has significantly dropped in recent years. One driving force is technology advancements. Wider adoption of high-speed Internet has significantly reduced the amount of time of loading webpages. The increasing popularity of smartphones and tablet computers has also lowered the consumer’s perceived search cost. In addition, many retail platforms also engage in reducing the search cost of their customers. For example, Amazon.com has been continually improving its webpage design, thereby enabling sellers to demonstrate their products with multimedia content formats (e.g., info-graphics, audios, and videos). In 2014, Amazon.com permitted some qualified sellers to upload “video shorts” to their product pages. In 2017, it further opened up the “video shorts” to all third-party sellers. In 2009, Amazon debuted the camera search function in its mobile app, enabling consumers to shoot
a photo of an item to search for similar ones on Amazon.com. Recently, Amazon partnered with Samsung to incorporate this feature in the camera app of Samsung’s smartphones. Amazon has also been investing in the augmented-reality view technology. For instance, consumers can use the new technology to see how a watch on Amazon.com would look like around their wrists before buying it. Retail platform invest billions of dollars in reducing the consumer’s search cost. For example, in Q1 2016, Amazon spent over $1.2 billion on augmented reality and virtual reality, and a considerable fraction of this investment intended to improve consumers’ search experience.

Empirical academic research also suggests that the consumer’s online search cost has decreased over time. There are dozens of studies estimating the consumer’s online search cost for hotels, books, tablets, computer parts, etc. (Bajari et al. 2003, Blake et al. 2016, Chen and Yao 2016, De los Santos 2008, De los Santos et al. 2017, Ghose et al. 2013, Hong and Shum 2006, Jiang et al. 2017, Jolivet and Turon 2017, Koulayev 2014, Moraga-González and Wildenbeest 2008, Moraga-González et al. 2013, Santos et al. 2012). Most of them indicate that the consumer’s online search cost per item is between 1 and 10 US dollars. Figure 1 plots their estimated search costs against the year of their datasets. The estimated search cost tends to decrease over time, although they are for different product categories on different platforms and are obtained with different methods.

[Insert Figure 1 about here.]

It is not obvious why retail platforms would spend billions of dollars on lowering the consumer’s search cost. Although doing so can attract more consumers, it will also intensify the competition among sellers and hence reduce the platform’s referral fee revenue. Extant literature provides little explanation on why and when the platforms may want to lower the search cost.
Extant literature also provides little insight on how the search cost will influence the platform’s optimal referral fee decisions. Most of the studies either consider the case where the sellers sell directly to consumers, which completely ignores the role of retail platform, or treat the platform’s referral fee as an exogenous variable. Because the referral fee is a major contributor to a platform’s profit, it is of practical importance for the platform to understand how to optimally adjust its referral fee when the consumer’s search cost changes.

Besides directly reducing the consumer’s search cost, retail platforms also adopt other methods to make consumer search easier. For example, many platforms allow consumers to filter the search results based on certain product attributes, e.g., shoe size and color. However, consumers still need to search the information for other attributes that are harder to filter, e.g., shoe design and style. To our knowledge, the extant literature either ignores the filtering function or simply treats it as reducing the consumer’s search cost, except that Zhong (2017) considers a related setting of targeted search (We will discuss the difference between our paper and Zhong (2017) in Literature Review section). No research has studied how filtering affects the platform, third-party sellers, and consumers and how its effect is different from that of a reduction in the search cost.

In summary, several important questions have not been well studied by previous research:

- Why have many retail platforms been making considerable investments in reducing the consumer’s search cost, even though doing so may hurt the platform’s profit?
- How will the consumer’s search cost affect optimal pricing decisions of the sellers and the platform and their profits? Will the effects be different in the short term versus in the long term?
- How does filtering affects the platform, the sellers, and consumers? How is its impact different from that of a reduction of consumer’s search cost?
We develop a game-theoretic framework to address these research questions. Many sellers sell differentiated products on a retail platform where consumers sequentially search for these products. Similar to Wolinsky (1986) and Anderson and Renault (1997), consumers initially do not know the products’ prices or match levels (i.e., how well a product matches their preferences), and can learn them after incurring a search cost. A product’s match level consists of two parts: the filterable match level and the unfilterable match level. The platform’s filtering function allows consumers to costless learn a product’s filterable match level, but they still need to search for its unfilterable match level. The retail platform charges the sellers a percentage referral fee (which is also known as “commission” or “final value fee” in practice).10 The sellers then simultaneously set their retail prices. In our analysis, we derive the equilibria in two scenarios. The first scenario constitutes our benchmark, where the referral fee is exogenous, i.e., the platform does not adjust its fee when the consumer’s search cost changes. This setting is more reasonable in the short term when the platform has not adjusted its referral fee after the search cost changes. In the second scenario, the referral fee is endogenously decided by the platform, i.e., the platform optimally chooses its referral fee as the consumer’s search cost changes. This setting is more reasonable in the long term when the platform can adjust its referral fee responding to the change in search cost. By comparing the equilibrium outcomes in these two scenarios, we can determine how the effects of a search-cost change differ in the short term versus in the long term.

We highlight several interesting findings. First, contrary to the conventional wisdom that a lower search cost will intensify price competition and reduce the sellers’ profits, we show that when the search cost decreases, the sellers’ profits may increase, although the sellers receive less profit per unit sale. This is because a decrease in search cost can attract more consumers to the platform (rather than choosing the outside option) and hence expand the market demand.
Second, we find that the retail platform can always benefit from a decrease in the consumer’s search cost when it optimally sets the referral fee, although it may suffer when the referral fee is exogenous. When the referral fee is exogenous, a lower search cost will attract more consumers to the platform, but also intensify price competition between sellers and reduce the platform’s referral fee revenue per unit sale. Therefore, the platform’s profit can either increase or decrease in equilibrium. By contrast, by optimally adjusting the referral fee, the platform can expand its demand without heavily hurting its profit margin, so its profit always increases with a search-cost reduction. Our finding provides a possible explanation to why many retail platforms invest large amounts of money to reduce consumer’s search cost in reality.

Third, we investigate how the platform should adjust its fee as the consumer’s search cost changes. One may expect that because a lower search cost tends to intensify sellers’ competition and reduce the platform’s profit margin, the platform should compensate it by raising its referral fee. Interestingly, we find that in equilibrium the platform may choose to lower its referral fee if the reduction in search cost significantly increases the demand elasticity of the referral fee. In this case, reducing the search cost makes the platform, the sellers, and the consumers all better off. By contrast, when a search-cost reduction does not significantly increase the demand elasticity, the platform will find it optimal to increase its referral fee. In this case, the decrease in search cost can counterintuitively lead to higher retail prices. This result provides a possible explanation to the puzzle documented by previous research that the prices in very competitive markets can be maintained much higher than marginal cost even when the search cost is low (Clemons et al. 2002, Hortaçsu and Syverson 2004).

Lastly, we show that filtering has two opposite effects on the match level of the products searched and bought by consumers. On the positive side, consumers can narrow their search set
down to the products with better match on filterable attributes. On the negative side, because filtering reveals some uncertainty of the product match level, conducting a search will uncover less information in expectation and bring less benefit to consumers. The negative effect partially offsets the benefit of filtering and makes consumers search less. We also characterize the conditions when filtering will increase or reduce the equilibrium retail prices. Intuitively speaking, if the market demand tends to have a relative longer (shorter) tail after filtering becomes available, the competition between sellers will be alleviated (intensified) and the equilibrium retail price is likely to increase (decrease). In other words, the filtering function can either strengthen or soften the competition between sellers. These results suggest that filtering can have very different marketing consequences compared to a search-cost reduction, which will encourage consumers to search more and always intensify the competition between sellers.

Lastly, we show that our results are robust when consumers have heterogeneous search costs, when products have heterogeneous quality levels, and when the platform charges fixed (instead of percentage) referral fee. We also examine how the sellers show optimally choose their prices when consumers have heterogeneous search costs, and how the distribution of consumer’s outside options will affect the profits of the platform and sellers, as well as the platform’s incentive to invest in reducing search cost.

**LITERATURE REVIEW**

Our research is closely related to the literature on consumer search. Extensive literature has studied how the decrease in the consumer’s search cost can influence product prices, firms’ profits, and consumer welfare. Many theoretical studies show that prices will drop to the marginal cost when the consumer’s search cost diminishes to zero (Anderson and Renault 1999, Salop and Stiglitz 1977, Stahl 1989, Stigler 1961, Wolinsky 1986). Their predictions are supported by several
empirical studies showing that the Internet has intensified price competition and lowered prices in markets for insurance (Brown and Goolsbee 2002), books and CDs (Brynjolfsson and Smith 2000), and prescription drugs (Sorensen 2000). To frustrate consumer search, some sellers engage in obfuscation (Ellison and Ellison 2009) to blur the product’s price information. By contrast, there is evidence showing that many firms can still sell at prices considerably higher than marginal costs even in very competitive markets with low search costs (Clemons et al. 2002, Hortaçsu and Syverson 2004). Some of more recent analytical research argues that a decrease in search cost may not always lead to more intense market competition or lower profits. Kuksov (2004) suggests that a search-cost reduction may facilitate product differentiation and lead to higher prices and industry profit. Cachon et al. (2008) show that when the consumer’s search cost decreases, sellers may expand their product assortments, which can increase consumers’ willingness-to-pay for their most-desired products, leading to higher equilibrium price and profit. Some research on consumer search studies different features in search markets. Armstrong et al. (2009) study the implication of “prominence” in a search market. A prominent seller will be sampled first by all consumers in the search process. They show that the prominent seller will earn a higher profit than the non-prominent sellers even if their products have the same quality levels. When products are heterogeneous in quality, the highest-quality seller will have the highest incentive to become prominent. Recent research (Branco et al. 2012, 2016, Ke et al. 2016) has also considered the consumer’s decision on how much information to acquire for a single product or for a multi-period scenario.

Most of these studies assume that firms sell directly to consumers. By contrast, we analyze a setting where third-party sellers sell on a retail platform which charges a referral fee for all the sellers. An important research question of this paper is that how changes in search cost on the platform will affect the retail platform’s optimal referral fee and market competition. An exception
is Janssen and Shelegia (2015), who study consumer search in a distributional channel. In their model, a single manufacturer sells its product to two symmetric competing retailers at the same wholesale price, and consumers have perfect knowledge of product quality but need to search to find out the retailers’ prices. They show that the consumer’s lack of knowledge about the manufacturer’s wholesale price will make both the consumer and the manufacturer worse off, because the double-marginalization problem in the channel becomes more severe than if the manufacturer’s wholesale price is opaque to the consumer. Our article is different from Janssen and Shelegia (2015). First, we consider very different market settings. In their model, the manufacturer sells its homogeneous product to two symmetric retailers on the same wholesale-price contract, whereas in our model a large number of sellers sell their respective differentiated products on the retail platform which charges the sellers a percentage fee for access to customers. Second, in our framework, consumers know neither the product’s match level nor its price before their search, whereas in Janssen and Shelegia (2015) only price is not known ex ante (because both retailers sell the same product of known valuation).

To the best of our knowledge, there are only two analytical studies on how consumers search on retail platforms. Dukes and Liu (2016) examine how a platform should choose the optimal consumer search cost level when the consumer optimally decides how many sellers to search and how deeply to evaluate each of them. However, they do not consider the platform’s optimal referral fee decision. By contrast, one of our main research questions is how the change in search cost will affect the platform’s optimal referral fee. In addition, in our framework, consumers conduct sequential search for products, rather than simultaneous search in Dukes and Liu (2016). Zhong (2017) considers the setting where the platform knows partially about how products match each consumer’s preferences and adopts targeted search technology to show consumers only products
whose match levels are above a certain threshold. Zhong (2017) shows that an increase in the threshold is equivalent to a decrease in search cost when the threshold is not too high, which will intensify price competition and decrease the price in general. By contrast, if targeted search is very precise, consumers will have no need to search in equilibrium, making sellers essential monopolists and leading to higher prices and lower demand. Therefore, the platform wants to limit the precision of its targeted search, even if increasing the precision is costless. Our paper proposes that filtering can be a very different mechanism than targeted search in Zhong (2017). Filtering will reduce the products’ match-level uncertainty so consumers will enjoy less benefit per search. Conversely, targeted search technology will exclude less-relevant products from the search set so consumers will enjoy more benefit per search. These two functions also affect the equilibrium prices differently. Targeted search will be equivalent to a reduction in search cost and intensify competition for most of cases, and will alleviate competition between sellers only in extreme case where consumers search only one product in equilibrium. In contrast, filtering is different from a reduction in search cost and can alleviate competition in more general situations where consumers search multiple items in equilibrium. We also analyze research questions not considered by Zhong (2017), such as the effects of the consumer’s search cost and the platform’s optimal referral fee decision.

Our research also contributes to the general literature on online retail platforms. Research on retail platforms mainly focuses on two-sided markets (Armstrong 2006, Hagiu 2006, Rochet and Tirole 2003, 2005). Our research contributes to this literature by explicitly studying how consumer search cost will influence the platform’s pricing decision and profitability. We show that as the consumer’s search cost decreases, the platform’s profit always increases if the platform optimally adjusts its fee. Whether the platform should raise or reduce its fee depends on how the change in search cost affects demand elasticity.
**MODEL SETUP**

An online retail platform charges a percentage referral fee \( r \) for independent sellers to sell their products to consumers through the platform. There are \( n \) independent sellers selling differentiated products. Our analysis focuses on the case when \( n \) is large, so the probability that consumers run out of sellers to search is negligible. A consumer \( j \)’s utility of buying seller \( i \)’s product is \( u_{ij} = q_i - p_i + M_{ij} \), where \( q_i \) and \( p_i \) are the base quality and the price of product \( i \), and \( M_{ij} \) is the “match level” of product \( i \) to consumer \( j \), measuring how well product \( i \) matches consumer \( j \)’s preference. There are no systematic differences among sellers ex ante. In the main model, we examine the case where all sellers have the same marginal costs and base quality, i.e., \( c_i = c \) and \( q_i = q \), \( \forall i = 1, 2, \ldots, n \). An extension later in the article will examine the case of heterogeneous product quality. Consumer \( j \) also has an outside option with utility \( u_{0j} \), distributed with the cumulative distribution function (c.d.f.) \( F_0(u) \) and the probability distribution function (p.d.f.) \( f_0(u) \). Without loss of generality, we normalize the total number of consumers to 1. The base quality and the match level capture the consumers’ horizontal preference and their vertical preference, respectively. Hence, the sellers are horizontally differentiated in our model.

*Filtering*

Many retail platforms allow their customers to filter products based on certain product attributes. For example, if a consumer wants to buy a pair of Nike Lunarglide 8 running shoes, Amazon.com allows her to filter the search outcomes based on attributes such as shoe size, width, and color (See Figure 2(a) for an example). Filtering enables consumers to find products that match their preferences better on these attributes. We define these attributes as a product’s *filterable attributes*. In practice, however, filtering usually cannot exhaust all the product attributes. There
are some unfilterable attributes, e.g., shoe design and style, which consumers can learn only through searching.

[Insert Figure 2 about here.]

We decompose the match level, $M_{ij}$, into two parts: $M_{ij} = \mu_{ij} + m_{ij}$. The filterable match level, $\mu_{ij}$, captures how well the filterable attributes match the consumer’s preference. The unfilterable match level, $m_{ij}$, reflects how well the unfilterable attributes match the consumer’s preference. The filtering function on the platform enables consumers to costlessly learn the filterable match level, $\mu_{ij}$, before searching a product. $\mu_{ij}$ and $m_{ij}$ are independently distributed. However, consumers still need to search for a product’s unfilterable match level, $m_{ij}$. To avoid confusion, we terms $M_{ij}$ as the product’s aggregate match level henceforth.

In practice, the filters on the platform usually classify each filterable attribute into a finite number of categories. For example, Amazon.com classifies the color of men’s running shoes into 12 categories. In our model, $\mu_{ij}$ follows a discrete distribution with $K(\geq 2)$ possible outcomes. $\mu_{ij}$ is equal to the $k$-th-lowest-possible filterable match level, $\mu_k$, with probability $\phi_k$, where $\mu_1 < \mu_2 < \cdots < \mu_K$ and $\sum_{k=1}^{K} \phi_k = 1$. Without loss of generality, we assume $E[\mu_{ij}] = 0$, which implies that $\mu_1 < 0$ and $\mu_K > 0$. The c.d.f. and p.d.f. of $m_{ij}$ are $F(m)$ and $f(m)$, respectively.

We make several technical assumptions on the distributions of $m_{ij}$ and $u_{0j}$. First, $f(m)$ and $f_0(u)$ have supports $(m_{min}, m_{max})$ and $(u_{min}, u_{max})$, where $-\infty \leq m_{min} < m_{max} \leq +\infty$ and $-\infty \leq u_{min} < u_{max} \leq +\infty$, are twice continuously differentiable and strictly positive. Second, to guarantee existence of unique pure-strategy equilibrium, $F(m)$ is assumed to have a decreasing inverse hazard rate $h(m) = \frac{1-F(m)}{f(m)}$. Third, we assume $E[m_{ij}] > \max\{m_{min}, u_{min}\} + \tau$ to exclude
the trivial case that no consumers will search after the first search. Many commonly used distributions, e.g., normal distributions, uniform distributions, exponential distributions, and logistic distributions, satisfy these properties above.

Consumer search

Each consumer buys at most one product, and will either purchase from a seller on the platform or choose the outside option (not buying from any seller). A consumer a priori does not know a product’s unfilterable match level, $m_{ij}$, nor its price, $p_i$. We assume that consumers do not know $p_i$ ex ante (even after filtering) because in practice many online sellers do not immediately show their final transaction price until after the consumers visit their product pages or until the product is put in the shopping cart. For example, Ellison and Ellison (2009) document that many online sellers of computer parts on retail platforms may post a low price to attract consumers to visit their product pages and postpone showing consumers the shipping-and-handling cost, taxes or add-on fees. The final transaction price can be much higher than the posted price that consumers see in the beginning. Moreover, a seller may set different prices for different variants of a product (e.g., the same design of shoes with different colors), and sometimes the platform will put all these variants together within the same webpage and only show their price range or the minimum price. Consumers can find the exact price of a specific product variant only after further searching. Moreover, filtering and sorting by product prices are often ineffective in practice. For example, if one sorts the search results of “Nike Lunarglide 8” by prices from low to high (see Figure 2(b)), many irrelevant results appear at the top of the page. 20 out of the top 24 results are either non-Nike-Lunarglide-8 running shoes, or irrelevant products such as running socks and T-shirts.
Each consumer $j$ knows her utility of her own outside option $u_{0j}$ and the filterable match level of every product, $\mu_{ij}$. To find out $p_i$ and the exact value of $m_{ij}$ for a product, the consumer needs to incur a search cost $\tau$. The search cost may include the consumer’s time and effort in clicking the links, reading product instruction, understanding the information, and evaluating the product, etc.

A consumer can decide whether to shop on the platform. If she does, she search the sellers sequentially. Specifically, after each search the consumer learns the exact value of $m_{ij}$ and $p_i$ for the searched seller $i$, then she can decide whether to buy it. If the consumer buys a product from a seller, she will stop searching and exit the market, otherwise she can continue searching another seller or leave the market without buying anything. If the consumer continues searching, one can show that she will next search the seller with the highest $\mu_{ij}$ not yet searched. If there are multiple unsearched sellers with $\mu_{ij}$, she will be equally likely to choose one from them.

_Sellers, retail platform and time sequence_

The timing of the game is as follows: First, the retail platform sets a percentage referral fee $r \in (0,1)$ for all sellers. We assume that the platform’s marginal cost is zero. Then, given $r$, all sellers simultaneously decide their retail prices. For each unit of product $i$ sold at retail price $p_i$, the retail platform earns $rp_i$ and seller $i$’s profit is $(1 - r)p_i - c$. Last, consumers make search and purchase decisions.

Using backward induction, we determine the symmetric pure-strategy Nash equilibrium: given the platform’s referral fee $r$, in equilibrium all sellers will charge the same retail price, $p^*$. Let $p^*(r)$ denote the seller’s equilibrium retail price given the referral fee $r$, and let $r^*$ denote the platform’s optimal percentage referral fee. Consumers have rational expectations about the sellers’ prices, i.e., prior to a search they expect that the next seller’s retail price will be $p^*(r)$. 
EQUILIBRIUM ANALYSIS

We start by analyzing the consumers’ searching and purchasing strategies. Suppose that the platform’s referral fee is $r$ and the equilibrium retail price is $p^*(r)$. Let product $i$ be the last product that consumer $j$ has just searched and her utility of buying it is $u_{ij}$. Because the number of sellers ($n$) is large, consumers will only search sellers with the highest possible filterable match level, $\mu_K$. It follows from Wolinsky (1986) that consumer $j$’s optimal sequential-search strategy is to stop searching and purchase the last searched product $i$ if and only if conducting another search will increase her expected utility beyond $u_{ij}$ by an amount lower than the search cost $\tau$; otherwise she will continue searching. We have the following two results.

**RESULT 1. In a symmetric equilibrium where all sellers charge prices $p^*(r)$, if consumer $j$ faces product $i$ with $p_i = p^*(r)$ and $m_{ij}$, she will purchase product $i$ if and only if $m_{ij} \geq \bar{m}(\tau)$, where $\bar{m}(\tau)$ is defined by $\int_{\bar{m}(\tau)}^{m_{\text{max}}} (m - \bar{m}(\tau))dF(m) = \tau$.**

Result 1 suggests that $\bar{m}(\tau)$ is essentially the equilibrium acceptance threshold of the unfilterable match level: if consumer $j$ has searched product $i$ and finds its price to be $p^*(r)$, then she will stop searching and purchase product $i$ if and only if $m_{ij} > \bar{m}(\tau)$. Note that the threshold is uniquely determined by the search cost, $\tau$. In the rest of the article, we use $\bar{m}$ to represent $\bar{m}(\tau)$ for conciseness.

**RESULT 2. $\bar{m}$ strictly decreases in the consumer’s search cost $\tau$.**

Intuitively, when the search cost ($\tau$) becomes lower, searching another product becomes less costly to the consumer. Therefore, consumers will have a higher purchase threshold $\bar{m}$. 
Denote $Q = q + \mu_K$ for ease of exposition. It follows Wolinsky (1986) that seller $i$’s profit as a function of its price $p_i$ is:

$$\pi_i^S = \frac{\phi_K F_0(\bar{m} + Q - p^*(r))}{\phi_K n \cdot (1 - F(\bar{m}))} \cdot \frac{[1 - F(\bar{m} - p^*(r) + p_i)]}{\text{Prob(Consumer buys from seller $i$)}} \cdot \frac{[(1 - r)p_i - c]}{\text{Profit margin}}$$

(1)

where the superscript $S$ represents the seller.

The platform’s total demand, i.e., the number of consumers buying on the platform, is $D = F_0(\bar{m} + Q - p^*(r))$. The expected consumer surplus is $CS(\tau, r) = E_u[\max\{u_0, \bar{m} + Q - p^*(r)\}]$.

**Exogenous Referral Fee**

We first analyze the benchmark case when the referral fee $r$ is exogenous, that is, the platform’s referral fee does not change with the search cost. In practice, platforms cannot adjust the referral fee levels frequently. One reason is that the platforms usually need to make an announcement months before the fee change becomes effective. For example, on November 9th, 2016, Amazon announced that it would increase the referral fee for media products starting March 1st, 2017.12 Similarly, on February 26th, 2017, eBay announced an increase in its fee for certain products to be effective after May 1st, 2017. Another reason is that frequently changing the referral fee will increase the sellers’ risk and lead to confusion, distrust, and frustration among sellers. Therefore, it is more reasonable to assume exogenous referral fee in the short term.

**Sellers’ optimal decisions**

We use “$\tilde{}$” over variables to indicate the exogenous-referral-fee case.

**Lemma 1.** Given the platform’s referral fee $r$, the sellers’ equilibrium retail price is $\tilde{p}^* = \frac{c}{1 - r} + h(\bar{m})$, a seller’s per-unit-sale profit and total profit are $(1 - r)h(\bar{m})$ and $\tilde{\pi}_i^{S^*} =$
Lemma 1 summarizes the equilibrium retail price, the sellers’ profit, and the total demand given the percentage referral fee $r$. When $r$ increases, the platform charges a higher mark-up for a unit sale, so the retail price will increase in equilibrium. Thus the total market demand on the platform and the sellers’ profit will both decrease. Note that a seller’s per-unit profit is proportional to $h(m)$. Intuitively, a higher $h(m)$ corresponds to more intense competition among the sellers. If a consumer is searching a seller charging the equilibrium price, $\tilde{p}^*$, she will buy the product if and only if $m_{ij} > \bar{m}$. If this seller increases its price by a small amount to $\tilde{p}^* + \Delta p$, then the consumer will buy the product if and only if $m_{ij} > \bar{m} + \Delta p$. Thus, the small increase in price will reduce the seller’s unit sales approximately by a $\frac{f(\bar{m})\Delta p}{1-F(\bar{m})} = \frac{\Delta p}{h(\bar{m})}$ fraction. When $h(\bar{m})$ is high, a seller will have stronger incentives to increase its price because doing so will only reduce sales slightly.

**Lemma 2.** When the consumer’s search cost decreases, given that a consumer searches on the platform, the expected number of products that she will search before purchase will increase, and the expected aggregate match level of the product that she will purchase will also increase.

When searching for another product becomes less costly, consumers will stop searching at a higher match-level threshold, $\bar{m}_{\tau}$. Hence, they will search more products and purchase a product with higher $M_{ij}$ in expectation.

Proposition 1 summarizes how the equilibrium retail price, the market demand, and a seller’s profit will change as the search cost ($\tau$) decreases.
PROPOSITION 1. When the referral fee $r$ is exogenous, as the consumer’s search cost decreases ($\tau$ decreases), (1) the equilibrium price $\tilde{p}^*$ decreases ($\frac{\partial \tilde{p}^*}{\partial \tau} > 0$), (2) the equilibrium total market demand strictly increases ($\frac{\partial \tilde{D}}{\partial \tau} < 0$), (3) each seller’s expected profit $\tilde{\pi}_i^*$ and the platform’s expected profit $\tilde{\pi}_P^*$ may either increase or decrease.

One might intuit that a lower search cost will intensify the competition between sellers and reduce their prices and profits. We find that when the search cost decreases, although the sellers’ prices decrease, they may receive higher profits. This is due to a market expansion effect: a decrease in the search cost will make consumers more likely to choose to shop on the platform, so the seller’s market demand will increase. The platform’s profit may either increase or decrease in equilibrium.

Example 1. To explore in detail how the consumer’s search cost affects the sellers and the platform, we consider a numerical example where $Q = 0.5$, $m_{ij}$ follows the uniform distribution between -0.5 and 0.5, and the utility of the outside option $u_{0j}$ is uniformly distributed between 0 and 1. The inverse hazard function of $m_{ij}$ is $h(m) = 0.5 - m$. We also assume that the consumer’s search cost $\tau < \left(\frac{1 - c}{1 - r}\right)^2$, otherwise all consumers will search at most one product in equilibrium. One can easily show that $\bar{m} = 0.5 - \sqrt{2\tau}$ and the equilibrium retail price is $\tilde{p}^* = \frac{c}{1-r} + \sqrt{2\tau}$, which strictly decreases with the consumers’ search cost.

A seller’s expected profit increases with $\tau$ when $\tau < \left(\frac{1 - c}{1 - r}\right)^2$ and decreases with $\tau$ when $\left(\frac{1 - c}{1 - r}\right)^2 \leq \tau < \left(\frac{1 - c}{1 - r}\right)^2$. The platform’s profit increases with $\tau$ when $\tau < \left(\frac{1 - 3c}{1 - r}\right)^2$, and decreases with $\tau$ when $\left(\frac{1 - 3c}{1 - r}\right)^2 \leq \tau < \left(\frac{1 - c}{1 - r}\right)^2$. Therefore, in the case where the referral fee $r$ is exogenous,
both the firm’s profit and the sellers’ profit are the highest when the search cost \( \tau \) is medium. Figure 3 depicts how the platform’s and the sellers’ profits change with \( \tau \).

[Insert Figure 3 about here.]

**Endogenous referral fee**

In this subsection, we study the case where the retail platform endogenously chooses its referral fee to maximize its expected profit. In the long term, the platform can strategically adjust its referral fee to the changes in search cost, so it is more reasonable consider the case of endogenous referral fee. Denote \( r^*(\tau) \) the platform’s optimal percentage fee and \( \pi^P = \pi^P (r^*(\tau)) \) the platform’s optimal expected profit. We have the following result.

**Proposition 2.** When the platform endogenously sets the referral fee \( r \), a lower search cost always strictly increases the platform’s expected profit, i.e., \( \frac{d\pi^P}{d\tau} < 0 \).

A lower search cost may have either positive or negative impacts on the platform’s profit. On the one hand, a lower search cost can benefit the platform because it leads to a higher market demand. On the other hand, it tends to intensify price competition among sellers, which can reduce the platform’s profit per unit sale. Proposition 1 has shown that when the platform’s referral fee is exogenous, a search-cost reduction can either increase or reduce the platform’s expected profit. In contrast, Proposition 2 shows that the platform will always benefit from a lower search cost when it optimally chooses its referral fee so it can expand the total demand without heavily reducing its profit margin.

Proposition 2 suggests that if the retail platform can optimally adjust its referral fee in the long term, it should always try to reduce the consumer’s search cost if doing so is not too costly. The
result explains why retail platforms, such as Amazon.com, are willing to invest millions of dollars in improving the consumer’s search experience and reducing their search cost on the platform. Although the platform may see a drop in profit in the short term (with the referral fee fixed), it will see a profit increase in the long term when it optimally adjusts its referral fee levels.

Next, we study how the retail platform should optimally adjust its referral fee with the consumer’s search cost. Intuitively, a reduction in the search cost tends to intensify the competition among sellers and hence reduce the platform’s profit margin, so the platform would mitigate the profit-margin decrease by raising the referral fee. However, Proposition 3 shows that under some conditions, it may be optimal for the platform to reduce its referral fee as the consumer’s search cost decreases. Let \( \epsilon_{D,r}(r) \equiv \frac{\partial D}{\partial r} \cdot \frac{r}{D} \) be the platform’s demand elasticity of referral fee \( r \).

**Proposition 3.** When the consumer’s search cost \( \tau \) decreases (i.e., when \( \bar{m} \) increases), the platform’s optimal referral fee \( r^* \) will increase if \( \frac{\partial |\epsilon_{D,r}(r^*)|}{\partial \bar{m}} < \frac{-c r^*(\bar{m}) h'(\bar{m})}{(c r^*(\bar{m}) + h(\bar{m}))^2} \), and will decrease if \( \frac{\partial |\epsilon_{D,r}(r^*)|}{\partial \bar{m}} > \frac{-c r^*(\bar{m}) h'(\bar{m})}{(c r^*(\bar{m}) + h(\bar{m}))^2} \).

Proposition 3 characterizes the conditions under which the platform should raise or reduce its referral fee when the search cost decreases. If a decrease in search cost significantly increases the (absolute value of) demand elasticity, the platform will find it optimal to reduce its referral fee because it can significantly increase the total demand. Note that the lowered referral fee will reduce the equilibrium retail price but actually increase the sellers’ profit margin. As a result, a lower search cost is *all-win* for the platform, sellers and consumers if the platform chooses to reduce its referral fee in equilibrium. Example A1 in the Appendix provides a numerical example where it is optimal for the platform to reduce the referral fee as the search cost declines.
Similarly, if a decrease in search cost does not significantly raise the (absolute value of) demand elasticity, then an increase in the referral fee will only slightly reduce the demand on the platform. Hence, with a decrease in the search cost, the platform will find it optimal to raise its referral fee, leading to an increase in its profit margin. In this case, a decrease in the search cost will reduce the sellers’ profits and increase the equilibrium retail prices, making the consumers worse off as well.

Proposition 3 suggests that when the platform reduces the consumer’s search cost, it may also want to reduce or raise its referral fee level correspondingly, depending on how the demand elasticity changes. In practice, it is easy for the platform to reduce the referral fee. However, the platform may receive complaints from sellers and consumers when raising the referral fees. In practice, when the platform finds it optimal to raise the referral fees, it should try to alleviate the sellers’ and consumers’ dissatisfaction. For example, the platform may want to announce a soon-to-be-in-effect fee increase at the same time as it introduces new search features and technologies on its website (e.g., augmented-reality technologies), and the platform can communicate to sellers and consumers that the fee increase will enable the platform to cover the cost of developing and offering such new technologies.

**Example 2.** To further study how the search cost’s impact may be different when the referral fee is endogenous versus when it is exogenous, we consider the numerical example with the same distributions and parameters as those in Example 1.

**[Insert Figure 4 about here.]**

Figure 4(a) plots how the platform’s optimal referral fee and the equilibrium retail price changes with the search cost $\tau$. In Example 1 where the referral fee is exogenous, the reduction in
\( \tau \) will always reduce the equilibrium retail price, \( p^* \), because it intensifies the seller competition. Conversely, in Example 2 with endogenous referral fee, when \( \tau \) is already low, further decreasing \( \tau \) can lead to a higher \( p^* \). This is because the platform will increase its referral fee when \( \tau \) becomes lower, forcing the sellers to charge higher prices to cover their cost. In spite of the increase in retail price, the sellers’ profit per unit sale will decrease. In other words, the reduction in consumers’ search cost may intensify the double-marginalization problem in the channel and lead to higher final prices. Figure 4(b) depicts how the platform’s and the sellers’ profits will change with the consumers’ search cost, \( \tau \). Echoing Proposition 2, although the decrease in \( \tau \) can lower the platform’s profit in the case with exogenous referral fee, \( r \), the platform’s profit will always increase if it can optimally adjust \( r \).

**FILTERING**

This section studies how the filtering function on the platform can affect the consumers’ optimal search and the seller’s pricing strategies, and how its effect can be different from that of a reduction in search cost. To this end, we compare the equilibrium outcomes of the no-filtering case with that in the main model where filtering is available. In the no-filtering case, consumers do not observe a product’s filterable match level (\( \mu_{ij} \)) before searching, and searching a product informs a consumer of the aggregate match level \( M_{ij} = \mu_{ij} + m_{ij} \).

Let \( F_M(M) \) and \( f_M(M) \) denote the c.d.f. and p.d.f. of \( M_{ij} \). Note that \( \mu_{ij} = \mu_k \) with probability \( k \) and the c.d.f. of \( m_{ij} \) is \( F(m) \), so \( F_M(M) = \Pr(M_{ij} \leq M) = \Pr(\mu_{ij} + m_{ij} \leq M) = \sum_{k=1}^{K} \Pr(\mu_{ij} = \mu_k)\Pr(m_{ij} \leq M - \mu_k) = \sum_{k=1}^{K} \phi_k F(M - \mu_k) \), or equivalently \( F_M(M) = E_\mu[F(M - \mu)] \). This equation reveals the relationship between the distributions of \( M_{ij}, \mu_{ij}, \) and \( m_{ij} \). Intuitively, when the filterable match level is \( \mu_k \), the aggregate match level \( M_{ij} \) exceeds \( M \) if and
only if the corresponding unfilterable match level \( (m_{ij}) \) exceeds \( M - \mu_k \). Hence, the overall probability of \( M_{ij} > M \) will be the expected probability of \( m_{ij} > M - \mu \), where the expectation is taken with respect to the filterable match level, \( \mu \).

Notice that \( F_M(\cdot) \) is a convex combination of \( F(\cdot) \), so \( F_M(M) \) will be greater (smaller) than \( F(M) \) when \( F(\cdot) \) is “convex (concave) enough” around \( M \). Similarly, \( f_M(M) = \sum_{k=1}^{K} \phi_k [f(M - \mu_k) = E_\mu [f(M - \mu)] \), which will be greater (less) than \( f(M) \) when \( f(\cdot) \) is “convex (concave) enough” around \( M \). The inverse hazard rate of \( M \) is:

\[
h_M(M) = \frac{1 - F_M(M)}{f_M(M)} = \frac{E_\mu [1 - F(M - \mu)]}{E_\mu [f(M - \mu)]} = \frac{E_\mu [1 - F(M - \mu)]}{1 - F(M)} \cdot \frac{f(M)}{E_\mu [f(M - \mu)]} \cdot h(M)
\]

We assume \( F_M(M) \) is twice continuously differentiable and \( h_M(M) \) is decreasing. A casual observation of Equation 2 is that \( h_M(M) \) is greater than \( h(M) \) if \( 1 - F(\cdot) \) is “convex” enough and \( f(\cdot) \) is “concave” enough, i.e., \( f'(\cdot) \) and \( f''(\cdot) \) are sufficiently small. Similarly, \( h_M(M) \) is smaller than \( h(M) \) if \( f'(\cdot) \) and \( f''(\cdot) \) are sufficiently large. As we will show later, the relative magnitude between \( h_M(M) \) and \( h(M) \) plays an important role in determining how filtering affects the sellers’ pricing strategies.

*Consumer’s optimal search strategy*

First, we examine the consumers’ optimal search strategy under the no-filtering case. Similar to the main model, consumers will stop searching and buy the last product they searched if and only if its aggregate match level, \( M_{ij} \), exceeds the equilibrium acceptance threshold, \( \bar{M}_N \), where the subscript \( N \) indicates the no-filtering case. \( \bar{M}_N \) is uniquely and implicitly defined by

\[
\int_{\bar{M}_N}^{M_{max}} (M - \bar{M}_N) dF_M(M) = \tau.
\]
In the scenario without filtering, the consumer’s acceptance threshold for the aggregate match level is \( \bar{M}_N \). In the scenario with filtering, the threshold is \( \bar{M} = \mu_K + \bar{m} \). Proposition 4 compares \( \bar{M} \) and \( \bar{M}_N \) and illustrates how the filtering functionality on the platform affects the consumers’ optimal searching strategy. Note that the higher the acceptance threshold is, the more likely consumers can end up buying a product with better aggregate match level.

**Proposition 4.** Filtering will increase the consumer’s acceptance threshold of aggregate match level, but by less than \( \mu_K \), i.e., \( 0 < \bar{M} - \bar{M}_N < \mu_K \).

Filtering affects on the consumers’ acceptance threshold for a product’s aggregate match level in two opposite ways. First, filtering informs consumers of a product’s filterable match level and narrows their consideration set down to those products with the best filterable attributes \( (\mu_{ij} = \mu_K) \). This effect raises the consumer’s acceptance threshold for the total match level by \( \mu_K \), so consumers are more likely to end up buying products with better match levels. Second, filtering reduces the direct benefit of searching. Because filtering has already resolved some of the consumers’ uncertainty, conducting a search will uncover less amount of information of match levels and thus bring less benefit to consumers, *ceteris paribus*. As a result, consumers tend to search less, stopping searching at lower acceptance thresholds. Overall, the second effect only partially offsets the first effect, so the consumer’s acceptance threshold for \( M_{ij} \) will increase but by less than \( \mu_K \).

**Sellers’ pricing decisions**

Next we investigate how filtering affects the sellers’ pricing decisions and the profits of the sellers and the platform. We show that the equilibrium retail price in the no-filtering case is \( \bar{p}^*_N = \frac{c}{1-r} + h_M(\bar{M}_N) \), as compared to \( \bar{p}^* = \frac{c}{1-r} + h(\bar{m}) \) when filtering is available. Filtering will reduce the equilibrium price \( (\bar{p}^* < \bar{p}^*_N) \) when \( \frac{h_M(\bar{M}_N)}{h(\bar{m})} = \frac{h_M(\bar{M}_N)}{h(\bar{M}_N)} \cdot \frac{h(\bar{M}_N)}{h(\bar{m})} > 1 \). Earlier discussions reveal that,
when \( f'(\cdot) \) and \( f''(\cdot) \) are low, \( \frac{h_M(q_i)}{h(M_N)} \) is higher, so \( \bar{p}^* < \bar{p}_N^* \) is more likely. Conversely, filtering tends to increase the equilibrium retail prices if \( f'(\cdot) \) and \( f''(\cdot) \) are large.

To formally illustrate this point, we consider the “marginal” effect of filtering on the sellers’ optimal pricing strategies, i.e., where filtering reveals only an infinitesimal amount of the products’ match level information to consumers. In such a scenario, the magnitude of the filterable match level, \( \mu_{ij} \), is very small such that \( \max_{1<k\leq K} |\mu_k| \to 0 \). Proposition 5 characterizes when filtering can increase or decrease the sellers’ equilibrium prices.

**Proposition 5.** Suppose \( \max_{1<k\leq K} |\mu_k| \to 0 \).

1. If \( h^2(\bar{m})f''(\bar{m}) + 2h(\bar{m})f'(\bar{m}) + f(\bar{m}) < 0 \), filtering will increase the equilibrium retail prices, i.e., \( \bar{p}^* > \bar{p}_N^* \).
2. If \( h^2(\bar{m})f''(\bar{m}) + 2h(\bar{m})f'(\bar{m}) + f(\bar{m}) > 0 \), filtering will decrease the equilibrium retail prices, i.e., \( \bar{p}^* < \bar{p}_N^* \).

How to interpret the technical conditions about \( f(\cdot) \), \( f'(\cdot) \) and \( f''(\cdot) \) in Proposition 5 in business practice? Mathematically, a small \( f''(\cdot) \) indicates that \( f'(\cdot) \) will not increase fast within a certain range. Hence, if \( f(x), f'(x) \) and \( f''(x) \) are low at point \( x \), \( f(x) \) is low at \( x \) and will stay low when \( x \) increases. The discussion of Proposition 1 shows that when the filtering is available, if seller \( i \) marginally increases its price, the corresponding unit-sale decrease of this product is approximately proportional to \( f(\bar{m}) \). Hence, when filtering is available and \( h^2(\bar{m})f''(\bar{m}) + 2h(\bar{m})f'(\bar{m}) + f(\bar{m}) < 0 \), i.e., \( f(\bar{m}), f'(\bar{m}) \) and \( f''(\bar{m}) \) are sufficiently low, the product’s demand is insensitive to its price \( p_i \) and this sensitivity will remain low when \( p_i \) further increases. In other words, under the case of filtering, the product demand tends to have a relatively long tail.
Hence, filtering will alleviate the competition between sellers and raise the equilibrium prices. An example product category is one-of-a-kind niche products whose unique features are hard to filter, so some consumers can have very high valuation for the unfilterable attributes. For these products, the platform will be more likely to allow consumers to filter the search results because doing so can increase the retail prices and the platform’s revenue from the referral fee.

The reverse will happen when \( h^2(\bar{m})f''(\bar{m}) + 2h(\bar{m})f'(\bar{m}) + f(\bar{m}) > 0 \), i.e., when \( f(\cdot), f'(\cdot) \) and \( f''(\cdot) \) are sufficiently high. In this case, filtering will make the product demand more sensitive to price, i.e., it has a relatively short tail. Hence, competition between sellers will be stronger and the equilibrium retail price will decrease. An example product category is products whose major features can be filtered, thus the search outcomes are limitedly differentiated when filters are applied. For these product categories, the platform will be hesitant to adopt filtering because it would trigger keen competitions between sellers and reduce the profits of sellers and the platform.

Although both filtering and a reduction in search cost make consumer search easier, our analysis above suggests that they have very different marketing implications. For example, a reduction in search cost will always encourage consumers to search more products, but filtering will reduce the benefit of search and so consumers may search less. Moreover, when the search cost decreases, the competition between sellers will always be intensified and the equilibrium retail price will always decrease (for a given referral fee). In comparison, filtering can possibly soften the sellers’ competition and lead to higher retail prices, which is desirable to the platform.

**EXTENSIONS**

*Heterogeneous search cost*
Consumers are different in their search efficiency, knowledge related to the product, and opportunity cost of searching. This section investigates the case in which consumers are heterogeneous in their search cost, $\tau$. Specifically, let $\Phi(\tau)$ denote the c.d.f. of $\tau$, where $0 < \tau_{\text{min}} \leq \tau \leq \tau_{\text{max}}$, and $\bar{p}^*$ denote the equilibrium price when consumers have heterogeneous search costs. In addition, let $\tilde{p}^*_\tau = \frac{c}{1-\tau} + h(\bar{m}(\tau))$ denote the equilibrium retail price in the homogeneous-search-cost case where all consumers have the same search cost $\tau$.

How should a seller choose its price when facing consumers with different search costs? A naïve approach is to “weigh each consumer equally” and set the price to be $E_\tau[\tilde{p}^*_\tau]$, the average of the homogeneous-search-cost prices ($p^*_\tau$) weighted by the density of $\tau$. By contrast, Proposition 6 suggests that this naïve choice of price is suboptimal and the seller should “weigh low-search-cost consumers more” and charge a price lower than $E_\tau[\tilde{p}^*_\tau]$.

**Proposition 6.** When consumers have heterogeneous search cost, the seller’s optimal retail price is a weighted average of the homogeneous-search-cost prices, i.e., $\bar{p}^* = E_\tau[a(\tau)\tilde{p}^*_\tau]$. The weighting function $a(\tau)$ decreases with the consumer’s search cost, i.e., $a'(\tau) < 0$. Moreover, $\bar{p}^* < E_\tau[\tilde{p}^*_\tau]$.

Intuitively, because a low-search-cost consumer is more likely to shop on the platform instead of the outside option, she is more likely to visit the seller than a high-search-cost consumer. Therefore, the distribution of a seller’s visitors is skewed towards low-search-cost consumers, so the seller should better target these consumers by charging relatively lower prices.

We also examine a numerical example with heterogeneous consumer search cost, where $\tau$ is uniformly distributed on the interval $(0, \bar{\tau})$. We show that all the major results in the homogeneous-search-cost model are qualitatively robust. Please refer to the Online Appendix for details.
Asymmetric Product Quality Levels

The product and service quality levels can vary among sellers on the platform. To capture the quality heterogeneity, we assume that there is one premium seller selling a premium product with a higher base quality level $q_H$, and the other $n - 1$ non-premium products have a lower base quality level of $q_L$. Let $\Delta q = q_H - q_L > 0$ be the quality gap between the premium product and the non-premium product. The marginal costs of these two types of products are $c_H$ and $c_L$, respectively. We assume $c_H - c_L < \Delta q$, so the premium seller is relatively cost effective. Without loss of generality, seller $i = 1$ sells the premium product, and sellers $j = 2, \ldots, n$ sell non-premium products. For tractability, we consider the case where consumers cannot filter the search outcomes, i.e., $\mu_i = 0, \forall i$.

In the Online Appendix, we show that consumers’ optimal search strategies depend on their outside options. Similar to the main model, if a consumer’s outside option is low, she will search the premium product first and, if its match level is low, continue searching non-premium products. If a consumer’s outside option is high, she will choose the outside option and not search any product on the platform. However, the search pattern for consumers with intermediate outside options is different from the main model where all products have homogeneous base quality. These consumers will search only the premium product and if its match level is low, they will choose the outside option. For these consumers, searching a premium product is better than the choosing the outside option in expectation, but the benefit of searching a non-premium product does not justify the search cost.

We first examine the premium seller’s pricing strategy. Let $\tilde{p}_1^*$ and $\tilde{p}^*$ be the equilibrium prices of the premium product (product 1) and the non-premium products, respectively. In the Online
Appendix, we prove that $\bar{p}^* < \tilde{p}^*_1(r) < \bar{p}^* + \Delta q$, i.e., the premium seller will charge higher prices than non-premium sellers, but the price difference will not exceed their quality difference so consumers will search the premium seller first. This result is similar to Armstrong et al. (2009), who find that the higher-quality firm has stronger incentive to become prominent, i.e., being searched first by consumer. However, their model assumes that consumers will always search the prominent product first, even though the consumers could be strictly better off in expectation by searching other items first. By contrast, the search sequence in our model is not exogenously imposed but endogenously determined by the consumer’s optimal decisions.

Next, we examine the non-premium sellers’ pricing strategies. Intuitively, when the premium product’s quality ($q_H$) becomes higher, the level of quality differentiation between premium and non-premium sellers will increase, leading to higher equilibrium prices of the non-premium products ($\bar{p}^*$). By contrast, Result 3 suggests that $\bar{p}^*$ is independent of $q_H$.

**Result 3.** *The equilibrium retail price of the non-premium products is $\bar{p}^*(r) = \frac{c}{1-r} + h(\bar{m})$, which is independent of the base quality level of the premium product.***

The intuition is as follows. The consumer’s optimal search strategy indicates that consumers will always search the premium seller first before they search the non-premium ones. Hence, the price and the quality level of the premium product will affect the number of consumers proceeding to search the non-premium products. However, if a consumer has searched the premium product and decided to continue searching the non-premium sellers’ products, she will never buy the premium product in equilibrium. Thus, given a consumer has decided to search non-premium sellers, the premium product’s base quality and price will not affect the consumers’ probability of buying from a specific non-premium seller. Therefore, the optimal price of non-premium products will be independent of the price and base quality of the premium product.
We also analyze a numerical example in the Online Appendix and show that both the premium seller’s and the non-premium sellers’ optimal prices will decrease when the consumer’s search cost (τ) decreases. When the platform’s referral fee is exogenous, the profits of the premium seller, the non-premium sellers, and the platform can either increase or decrease with the search cost. When the platform endogenously chooses r, its optimal profit will always become higher when τ decreases. Moreover, the platform’s profit will always increase with the base quality levels of the premium product and the non-premium product, qH and qL. Thus, our results in the main model are robust when products have heterogeneous base quality levels.

Fixed referral fee

In the previous analysis, we assume that the platform charges a percentage referral fee for the sellers. In practice, some retail platforms may charge a fixed amount of referral fee for each unit sale. Here we examine whether our major results are robust to this alternative referral-fee structure. The platform charges a fixed referral fee, d > 0, per seller’s unit sales, instead of the percentage fee, r. All other model settings remain the same.

In the Online Appendix, we analytically show that most of the previous results in the percentage-referral-fee setting can be qualitatively replicated in the fixed-referral-fee setting. A decrease in the search cost will reduce the equilibrium retail price and increase the demand on the platform. The profits of the sellers can either increase or decrease. When the platform can endogenously choose the referral fee, d, a lower search cost will always increase the platform’s profit. When the consumer’s search cost decreases, the platform will optimally increase its referral fee if and only if the reduction in search cost does not raise the demand elasticity of the referral fee significantly. Overall, most of our results are robust to different referral-fee structures.
Outside option and retail platform competition

In practice, consumers can choose whether to shop on our focal retail platform or on some other competing platforms, and the latter can be considered as choosing the outside option in our model. Hence, our analytical framework can partially capture the competition between different retail platforms (e.g., Amazon.com versus eBay.com) although we do not explicitly consider the competitors’ pricing decisions. When the focal platform faces stronger competition, consumers are more likely to receive a better outside option. This extension analyzes the influence of outside option by considering a family of outside-utility distributions which differ only in their locations.

Let the distribution of the outside option be $F_{0,l}(u_0) = F_0(u_0 - l)$, where a larger $l$ indicates that the outside option tends to be more attractive, i.e., the competing platform is stronger. For tractability, we assume that the platform endogenously chooses its fixed referral fee, $d$. We continue to adopt the distribution assumptions in Example 1 and 2: $Q = 0.5$ and $m_{ij} \sim Uniform(0,1)$. The consumer’s outside option, $u_0$, follows a uniform distribution between $l$ and $1 + l$. We consider the nontrivial case with $-2\sqrt{2}\tau - c < l < 1 - 2\sqrt{2}\tau - c$, otherwise either no consumers or all consumers will shop on the platform.

We show that in equilibrium, the platform’s optimal referral fee is $d^* = \frac{1 - 2\sqrt{2}\tau - c - l}{2}$, a seller’s profit is $\pi_i^S = \frac{(1 - 2\sqrt{2}\tau - c - l)^2}{2n} \sqrt{2\tau}$, and the platform’s profit is $\pi_p^S = \frac{(1 - 2\sqrt{2}\tau - c - l)^2}{4}$. When the platform faces stronger competition, i.e., $l$ is larger, it will charge a lower referral fee, and its profit as well as the sellers’ will decline. The platform can always benefit from a lower search cost: $\frac{\partial \pi_p^S}{\partial \tau} = \frac{1 - 2\sqrt{2}\tau - c - l}{\sqrt{\tau}} < 0$. 
Note that the absolute magnitude of the above derivative decreases with $l$. To put it differently, when the platform competes with stronger competitors, it will receive less benefit from reducing the consumer’s search cost. This result may sound surprising because one might conjecture that a platform facing stronger competition would be more inclined to lower its search cost in order to poach customers from competitors. However, our result suggests that a platform facing weaker competitors ($l$ is larger) will have a stronger incentive to reduce its search cost because it has a higher profit per unit sale. This result explains why the largest retail platforms (e.g., Amazon.com and Overstock.com) invest heavily in search-cost-reduction technologies, e.g., camera search, barcode search, and augmented-reality view technologies, whereas smaller shopping sites usually use less advanced search technologies. This will create a Matthew effect, allowing larger platforms to offer better search experience and attract even more customers.

**CONCLUSION**

This article studies how the consumer’s search cost influences an online retail platform and independent sellers on the platform. We explicitly model the pricing decisions of both the platform and the sellers. We show that when consumers search for both the price and the match level of products, a lower search cost will reduce the equilibrium retail price due to stronger competition, but the seller’s expected profit may actually increase. This is because a lower search cost attracts more consumers to shop on the platform instead of choosing the outside option. When the referral fee is exogenous, the platform’s profit may either increase or decrease as the consumer’s search cost decreases. However, when the platform endogenously chooses its referral fee, its expected profit will always increase as the search cost decreases. This result implies that the platform should always try to reduce the consumer’s search cost as long as doing so is not too costly.
Our analysis shows that when the consumer’s search cost decreases, the platform should reduce its referral fee if the demand elasticity of the referral fee significantly increases, otherwise the platform should raise the referral fee to increase its profit margin. If a lower search cost reduces the platform’s optimal referral fee, sellers will pay less to the platform for a unit sale, leading to a lower equilibrium retail price yet higher expected seller profits. In this case, a lower search cost is all-win for the platform, sellers and consumers. In contrast, when a lower search cost increases the platform’s optimal referral fee, the equilibrium retail price may increase but the seller’s profit margin will shrink. Hence, a lower search cost can make both sellers and consumers worse off.

We also consider how the filtering functions affect the consumers’ search and the sellers’ pricing decisions. We show that, after filtering becomes available, consumers can filter out the products with better filterable attributes and hence are more likely to find a product with a better match levels. At the same time, because filtering has already partially resolved consumers’ uncertainty, conducting a search will uncover less amount of information and generate less benefit for consumers. Hence, consumers will be less willing to search and tend to buy products with less good match. We also characterize the conditions when filtering will increase or reduce the sellers’ equilibrium prices. If the market demand to have a relative longer (short) tail when filtering is available, the competition between sellers will be alleviated (intensified) and the equilibrium retail price tends to increase (decrease). These results suggest that filtering can be very different from a search-cost reduction, for the latter always induces the consumers search more and leads to stronger competition among sellers.

Even though we assume that each seller’s product is unique, our model can conceptually apply to the case where some sellers sell a common branded product. In essence, a product in our model is the totality of the core product and any seller attributed together as a whole. So, the differentiation
among “products” comes from not only the core product attributes (e.g., shoes of different brands, style, color, size, etc.) but also the sellers’ attributes (e.g., services, return policy, existence of physical stores close to the customers, etc.). For example, on Amazon.com, even in cases where sellers sell the same branded shoes of a particular model/design, often a shoe seller carries only limited color-size combinations, and different sellers can carry different color-size combinations. In addition, sellers may be differentiated based upon the services they provide. For example, sellers on the east coast of the U.S. can ship their products to New York City within two days, but it may takes several days to ship to Los Angeles. Similarly, sellers on the west coast of the U.S. can ship products to Los Angeles faster than to New York City. Furthermore, whether the sellers have physical stores close to the customers can differentiate the sellers among consumers, because consumers may have more convenient options for product returns or exchanges when a seller has physical stores close to the consumer.

We would like to point out a few caveats about our model. In our analysis, we do not explicitly study how sellers’ entry decisions can be affected when the consumer’s search cost changes. However, one can easily extend our model to analyze how the search cost affects sellers’ entry on the platform. For example, one can assume that a seller needs to incur some positive fixed cost to sell on the platform. If in our model a seller’s expected profit increases when the consumer’s search cost decreases, then in that parameter region it will be more likely to observe sellers entering the market. Similarly, if a lower search cost reduces the seller’s expected profit, then it is likely that some sellers will exit the market.

We have assumed that each seller sells only one product. In practice, a seller may sell multiple differentiated products on the platform. One can study how the consumer’s search cost affects the seller’s product assortment decisions. Cachon et al. (2008) show that when sellers sell directly to
the consumer, they will increase their product assortments when the consumer’s search cost decreases. We conjecture that if the sellers sell their products through a retail platform, a decrease in the consumer’s search cost will increase sellers’ product assortments when the referral fee is exogenous. However, when the referral fee is endogenous, if a lower search cost induces the platform to increase the referral fee, sellers may provide fewer assortments as a result.
APPENDIX

Example A1. This example presents a case where the platform’s optimal percentage referral fee $r$ can decrease when the consumer’s search cost decreases. Suppose that $q = 2, c = 1, u_{0j}$ follows the student-t distribution with degree of freedom 5, and $m_{ij}$ follows a logistic distribution with c.d.f. $F(m) = \frac{1}{1+e^{-5m}}$. The platform’s optimal referral fee is shown in Figure A1. When $\bar{m} < 3.5$, the platform’s optimal referral fee will decrease as the consumer’s search cost decreases.

[Insert Figure A1 about here.]

REFERENCES


Brown, Jeffrey R. and Austan Goolsbee (2002), "Does the Internet Make Markets More


Commerce, U.S. Department of (2017), *U.S. Census Bureau News*


PwC (2015), *Total Retail 2015: Retailers and the Age of Disruption*


**Footnotes:**

1. [https://www2.census.gov/retail/releases/historical/ecomm/17q1.pdf](https://www2.census.gov/retail/releases/historical/ecomm/17q1.pdf)
4. [https://www.amzproductvideo.com/pages/how-it-works](https://www.amzproductvideo.com/pages/how-it-works)
Different articles present estimated search costs in different formats. We use the median of their estimates whenever possible because the distributions of many estimates have long tails for very high search costs. For articles only reporting the range of the estimated search cost, we use the midpoint of the range. We take natural logarithm to mitigate the impact of extreme values.

In a later extension, we show our results are robust if the platform charges fixed referral fees. If $E[\mu_{ij}] \neq 0$, one can redefine a “demean-ed” new filterable match level $\mu'_{ij}$ by subtracting $E[\mu_{ij}]$ from $\mu_{ij}$. Specifically, let $q' = q + E[m_{f,ij}]$ be the new quality level, and $\mu'_{ij} = \mu_{ij} - E[\mu_{ij}]$ be the new filterable match level, whose expectation is zero. The new model will be equivalent to the model we present in the main text.

Without loss of generality, we assume the consumer with the largest search cost ($\tau = \tau_{\text{max}}$) will search on the platform with positive probability.

The expression of $a(\tau)$ is given in the Online Appendix.
Figure 1  Estimated Search Cost vs Dataset Time

![Graph showing the estimated search cost vs dataset time with a downward trend.]

Figure 2(a)  Screenshot of Search Results of “Nike Lunarglide 8” on Amazon.com

Figure 2(b)  Screenshot of Search Results of “Nike Lunarglide 8” on Amazon.com, Sorted by Option “Price: Low to High”
Figure 3  Seller’s and Platform’s Profits

Note. This figure is plotted using $c = 0.05$, and $r = 0.2$. The curves are rescaled to be fit in the same figure.
Figure 4  Numerical Example with Endogenous Referral Fee

(a) Equilibrium Referral Fee and Retail Price

(b) Seller’s and Platform’s Profit

Note. This figure is plotted using $c = 0.05$. The curves are rescaled to be fit in the same figure.

Figure 5  Seller’s Profit, Platform’s Profit and Optimal Referral Fee

Note. This figure is plotted using $q = 5$ and $c = 1$. The platform’s and the seller’s expected profits are rescaled to fit both curves in the same figure.
Figure 6  Platform’s Optimal Referral Fee

Note. This figure is plotted using $q = 5$ and $c = 1$.

Figure 7  Seller’s and Platform’s Profits When Referral Fee is Exogenous vs. Endogenous

Note. Figure 6(a) is plotted using $q = 5$, $c = 1$ and $r = 0.33$. Figure 6(b) is plotted using $q = 5$ and $c = 1$. The platform’s and the seller’s expected profits are rescaled to fit both curves in the same figure.
Figure 8  Consumer’s Equilibrium Search Strategy

Search product 1 and buy it

Search product 1 first and continue searching other products

Not search on platform

$m_1 j$

$m$

$m - \Delta q + p_1^* - p^*$

$u_0^b$

$u_0^s$
Figure A1  Optimal Referral Fee