Online Marketplace Advertising

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Abstract

This paper considers the allocation of "shelf space" in the context of online marketplaces, where items' positions are linked to advertising. While featuring advertised products makes search less efficient, lowering transaction commissions, it incentivizes sellers to compete for better placements via advertising. We consider this trade-off by modeling both sides of the platform. On the demand side, we develop a joint model of search (impressions), consideration (clicks), and choice (demand). On the supply side, we consider sellers' advertising competition under various fee structures and ranking algorithms.

Using buyer, seller, and platform data from an online marketplace specializing in handmade goods, we find that sorting goods by consumer preferences decreases platform profits, as it leads to more lower price item purchases. On the seller side, the high advertising commissions create an incentive for sellers to advertise items in the hope of selling them elsewhere with lower fees. Reflecting this hope, there is a negative valuation from demand for the sellers who advertise, whereas the median valuation for consideration is estimated to be \$0.13. We find that both the platform and its sellers are better off when the platform lowers the cost-per-action (CPA) and instead increases the cost-per-consideration/click (CPC).

Keywords: Online advertising, E-commerce, Two-sided market, Sequential search model, Dynamic discrete choice model

JEL Classification Codes: M31, M37, L11, L81, D83, C61

1   Introduction

Online marketplaces are economically consequential and growing. The market capitalization of Alibaba, the world's largest online marketplace, is around \$190 billion, and that of Amazon, the largest online retailer in the US, is over \$330 billion in the second quarter of 2016. Amazon sold more than 2 billion items worldwide in 2015 and approximately 50% of the units were sold by more than 2 million third-party sellers (or called marketplace sellers).[1] It is now believed that an important part of Amazon's business future is being the world's biggest online retailer acting as a platform for goods.[2] With recent developments in mobile website browsing, online marketplaces are expected to continue the rapid growth in coming years.[3]

With buyers on one side, and third party merchants on the other, online marketplaces are a two-sided platform (Rochet and Tirole 2003, Armstrong 2006, Weyl 2010) of substantial economic importance. In this paper we address both sides of the platform by considering i) how online marketplace shelf space allocation decisions (i.e., the listings' ranks) affect the consumers' search (impression), consideration (click) and demand for merchant goods, and ii) how payments for better allocations affect advertiser behavior and profits for both the advertiser and the platform. Advertiser payments are a growing source of revenue for these marketplaces; owing to its wealth of consumer knowledge, Amazon is now the seventh largest seller of online advertisements worldwide, exceeding Twitter, Pandora and LinkedIn.[4] Accordingly, we discuss both sides of the platform and their attendant implications for platform strategy next.

1.1   Consumer Search, Consideration and Choice in Marketplaces

There has been considerable attention allocated to search and purchase, both in theoretical (Stigler 1961, Stahl 1996, Baye and Morgan 2001, Janssen and Moraga-González 2004) and empirical work (Mehta et al. 2003, Hong and Shum 2006, De los Santos et al. 2012, Honka 2013, Kim et al. 2010, Chen and Yao 2014, Koulayev 2013, Moraga-González et al. 2012). In online environments, empirical research has mostly focused on the demand side of the platform (Kim et al. 2010, Koulayev 2013, Ursu 2015), price elasticity of demand and price dispersion amongst internet retailers (Chevalier and Goolsbee 2003, Ellison and Ellison 2009, Smith and Brynjolfsson 2001, Einav et al., 2013a), or recommendation system (Bodapati 2008, Ansari et al. 2000).

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[1]http://seekingalpha.com/article/3962561-amazon-com-third-party-sellers-drive-profitability
http://www.statista.com/statistics/259782/third-party-seller-share-of-amazon-platform/

[2]http://www.wired.com/business/2013/01/amazons-future-not-selling-stuff/,

[3]Other examples of online marketplaces include Etsy, Yahoo! Shopping, eBay, Overstock, CafePress, Zazzle, Oodle, eCrater, Bonanzle and Fancy.

[4]http://www.seattletimes.com/business/amazon-easing-into-1b-sideline-business-ad-sales/

We advance this literature by i) making search order (at least partially) exogenous to the consumer and under control of the firm, ii) interleaving consideration (or the clicking) of items between search and choice. This sequential process of search, consideration and choice is often denoted a consumer purchase funnel. Hence, we extend existing models of online consumer search (e.g., Koulayev 2013) to accommodate the entire purchase funnel including consideration.

By analyzing the entire purchase funnel and the nature of information available only upon clicking, we can address a number of demand side questions relevant to the marketplace. These include i) the trade-off between placing an organic product of consumer's best interest versus an advertised good and ii) which information should be presented to consumers on the product listing page versus product detail page.

1.2 Platform Fees, Position Allocation Decisions and the Implications for Merchant Advertising

Our paper is related to an important literature on efficiently allocating limited shelf space in grocery markets. These include papers on slotting fees (Bloom et al. 2000, Sudhir and Rao 2006), shelf placement (Dréze et al. 1995), and display allowances (Drèze and Bell 2003). In the context of online marketplaces, better placements in the form of appearing earlier in the rankings, lead to more exposures, considerations and choices. The slot spaces are allocated in part via advertising fees, and the sellers increase advertising spend to obtain more favorable listing positions.

There is also a large body of research concerning advertising in media markets including Dukes and Gal–Or 2003, Anderson and Coate 2005 and Wilbur 2008. The literature regarding online markets has focused on search engine advertising (Yao and Mela 2011, Rutz and Bucklin 2011, Yang and Ghose 2010, Katona and Sarvary 2010, Chan and Park 2015) and more recently on display advertising (Johnson 2013, Wu 2015, Lu and Yang 2016), where advertisers decide how much to bid for a keyword or a placement based on their beliefs about consumer clicks and toughness of competition. We build on this work by studying sellers' advertising decisions in an online marketplace platform, where consumers make search, consideration, purchase decisions (i.e. entire purchase funnel), sellers compete for limited spaces available within the consumer search length, and the platform maximizes revenue from various fee types.

Online marketplaces vary widely in their choices of fee structure, and their revenue models are often built upon several different fee types. Commonly seen fee types include (i) listing fees, which are entry costs in that they are paid to the platform when listing an item, but

before the actual sale takes place;[5] (ii) commissions on sales, which are usually charged per item as a percentage of the total sale amount, and vary between $6\% \sim 25\%$ depending on the website and categories;[6] (iii) advertising fees, which are optional as sellers who opt-in for advertising to either gain better placement or more exposures pay these additional fees. These three types of fees are commonly characterized by the cost on the completed transactions (or cost-per-action, CPA), or clicks made by the consumers (or cost-per-click, CPC), or mere impressions delivered to the consumers (or cost-per-mille, CPM).[7] Of central note, these three fee types map directly to the consumer purchase funnel described above; CPM pertains to exposures from search, CPC to clicks, and CPA to transactions made.

Accordingly, optimal advertiser behavior depends on how consumers' search, consideration and choice respond to advertising and the fee structure of the site. With CPA, there exists a large incentive for the sellers to redirect consumers to sites with no commissions, such as the sellers' own sites. Via the sellers' effort to redirect consumers, the online marketplace shoppers are encouraged to web-room. "Web-rooming", the practice of conducting research online to take advantage of the information and the product assortment available (e.g., reviews) before buying in-store or on another site, is a more common phenomenon than the well known "show-rooming" effect, and is becoming the newest challenge for the online marketplaces.[8][9] One approach to mitigate the web-rooming effect is to restrict merchants from redirecting.[10] An alternative approach is to realign sellers' economic incentives with an alternative fee structure. For example, the online marketplace may reduce sellers' redirecting incentives by lowering CPA, and instead charging fees based on CPC and/or CPM. The latter is the strategy pursued in this research. Optimal advertiser behavior also depends on the competition between advertisers for limited shelf spaces (available slots) on the platform.

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[5]For example eBay charges $0.03 \sim \$0.05$ per listing if an individual lists more than 50 items per month.

[6]Amazon, for example, charges 15% of the transaction price in average + $0.99 per item (or pay a monthly subscription fee of $39.99 and $0.99 per item fee is waived).

[7]As for the advertising fees, Amazon uses an auction-based pricing model for each keyword, similar to keyword search engines. Etsy asks sellers to list several keywords and set one weekly maximum budget. Both charge sellers on a cost-per-click basis. On the other hand, the website in our empirical application asks sellers about the willingness to pay extra 17% of the sale price when the item is sold, and the platform has full discretion on how the sponsored products are displayed.

[8]In this paper, we interpret web-rooming effect broadly, and include buying in seller's own website or blog, after browsing and gathering information in online marketplaces.

[9]http://www.wiser.com/infographic-webrooming, http://www.adweek.com/news/advertising-branding/study-shows-prevalence-consumer-webrooming-157576

[10]The first clause in Amazon's selling policies under prohibited seller activities is "attempts to divert transactions or buyers", and Amazon monitors and takes strict measures on infringements. (www.amazon.com/gp/help/customer/display.html/ref=hp_rel_topic?ie=UTF8&nodeId=200414320) The website in our empirical application currently overlooks sellers including hyperlinks, URLs, phone numbers, or web addresses. The discussion with the firm revealed that the web-rooming effect is the major concern for the company.

When one advertiser moves up in the rankings, others move down interdependently. Hence there is an incentive to respond to the advertising moves of other merchants, and we consider this competition when exploring the effect of a site's fee structure and ranking algorithm on its revenue.

By modeling advertiser behavior, we are able to address a number of other policy related questions of value to the site. These include i) how the changes in product placement with respect to advertising (the ranking algorithm) affect the advertiser and platform profits, and ii) how advertising fees should be set and potentially mitigate the web-rooming effect.

1.3 Summary

In sum, we contribute to a sizable and growing empirical literature on two-sided markets (Armstrong 2006, Argentesi and Filistrucchi 2007, Fradkin 2014) by considering the context of an online marketplace. We are aware of no empirical papers that jointly consider the advertiser competition on the supply side of the online marketplace in conjunction with the consumer purchase funnel. Key aspects distinguishing online marketplace platform from other two-sided markets such as keyword or display advertising markets, are its ability to collect both transactional and advertising revenue. In this context, the platform's optimal marketing strategies inevitably depend on both consumers' demand and sellers' competition on the platform. An integrated model of both sides of the network is important because policies that enhance revenue on one side often decrease revenue on the other. In light of limited work that combines both sides of the network in the context of online marketplaces, our goal is to jointly consider both sides in order to understand how the online marketplace's advertising policies, specifically the ranking algorithm and the fee structure, affect the welfare of sellers, consumers and the platform.

Owing to our policy oriented goals, we take a structural approach in modeling agents' behaviors.[11] Recovering primitives of consumer preferences and advertiser valuations enable us to examine the potential market outcomes under counterfactual environments. We apply our model to a unique data set where craft merchants sell goods on a platform to consumers. We observe consumer search, consideration and choice on the demand side, advertiser decisions on the supply side, and the fees charged and ranking algorithm used by the platform.

Our demand side model suggests that information on price (revealed outside on the

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[11]An alternative approach is to test various pricing policies with A/B experiments. There are a number of limitations inherent in this approach. First and foremost, changing the online marketplace's advertising policies shifts their fundamental business model, potentially irreversibly. For some sites, this sort of variation could prove especially costly. Second, owing to limited cells, A/B testing can capture only a fraction of the decision space across fees and ranking algorithms. Third, a structural approach provides a theoretical foundation to underpin changes in agent behavior.

product listing page) and the number of pictures (revealed inside the product detail page) matter most in consumer preferences. The consideration (click) cost is estimated to be about 9 times larger than the search (impression) cost, and there exists considerable heterogeneity across consumers. Owing to consumers' high level of price sensitivity, we further find that ordering the products by listing the highest utility product first leads to lower platform and seller revenues. Though more items are sold by reordering the search results, those that are sold are lower price items.

On the supply side we find that the seller's valuation from demand under the current fee structure is negative (-6% of the transaction amount) when the seller opts-in for advertising. In other words, sellers are worse off on each advertised sale. In contrast, the median valuation from consideration (click) is estimated to be \$0.13. Together, these results suggest that clicks play a role in generating sales off-site (via webrooming) or that these considerations have a branding value. Of note, impressions generate little value beyond clicks in our data. In addition, we find evidence of diminishing marginal returns for considerations and searches, consistent with the industry practice of "frequency capping". Because of the high value for clicks and low value for sales, policy simulations show that lowering the cost-per-action/fees (CPA) and increasing the cost-per-consideration/click (CPC) yield a "win-win" outcome for the platform and its advertisers.

This paper is organized as follows. Section 2 describes our data and highlights key features pertinent to online marketplaces. Next we present the model of buyers' purchase funnel decisions and sellers' advertising decisions. Section 4 discusses estimation method and identification argument, and Section 5 describes the estimation results. In Section 6, policy simulations are conducted to address questions that are interests to practitioners.

2   Data

In order to better motivate the model assumptions and development, this section overviews our data context, first discussing the platform, then the buyers and finally the advertisers.

2.1   The Platform

The data we use is furnished by a Korean online marketplace (the-nuvo.com) specializing in handmade goods. A unique aspect of the data is the depth of information provided by the platform on *both* buyers and sellers, along with their operational details including product display ranking algorithm. The context is well suited to our model because we observe search, consideration and choice, as well as advertiser behavior. Moreover, owing to the unique nature of the handcrafted items in the data, search and consideration are extensive, and

advertising has informative value making it an ideal context to assess the consumer purchase funnel and how it is affected by advertising. The data include several files, each discussed below.

2.1.1 Platform Structure

We consider three aspects of the platform structure: the design of its pages (i.e., how attributes are allocated across the product listing and product detail pages), the ranking algorithm used to display products to consumers, and the fees charged for advertising.

Website Design When a consumer first visits the site, they arrive on the main landing page. On this page, the platform displays 10 product listings in a sequential product feed format, of which a subset of items are visible depending on the size of the screen.[12] Consumers can scroll down to view more items or can interrupt search by clicking upon a specific product to access its product detail page and to gather additional information. Upon continuation of search, the platform loads 10 more products at a time in response to scroll down requests, and the main page product feed continues until the consumer stops searching. Because 10 products are loaded per request, we do not observe where the product search exactly ends within the loaded products. Thus in the empirical analysis, consumers are assumed to have searched all items that are loaded from the requests.[13]

Information included in the "*product listing page*" (defined as the product's information presented on the main landing page) includes the item's name, seller's (brand) name, price, number of likes, discount percentage if the product is on sale. All other product specific information is revealed in the "*product detail page*" (defined as the page returned after a click upon an item), including a detailed product description, additional pictures, questions and answers, user reviews, size/color/material options, customizability (e.g. personal engraving), quantities remaining, shipping methods, exchange and return policy, and the seller contact information.

Although the transactional site we consider has several categories, analogous to a retailer with many categories such as a department store, we focus our attention on items listed on the main landing page and subsequent listings returned as consumers scroll down the main landing page. This focal category selection arises from the institutional details of our setting where advertising works via the main page product feed ranking algorithm, whereas other

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[12]The format is similar to Facebook's news feed format but with pictures of products.

[13]The website also observes an "overlay" request when the consumer places the mouse on top of the product pictures. Hence, instead of assuming the consumer searches all of the last 10 items, we can define the search end as the last overlay within that set. Our estimates are robust to this alternative approach for inferring the end of search.

Figure 1:   Website Design
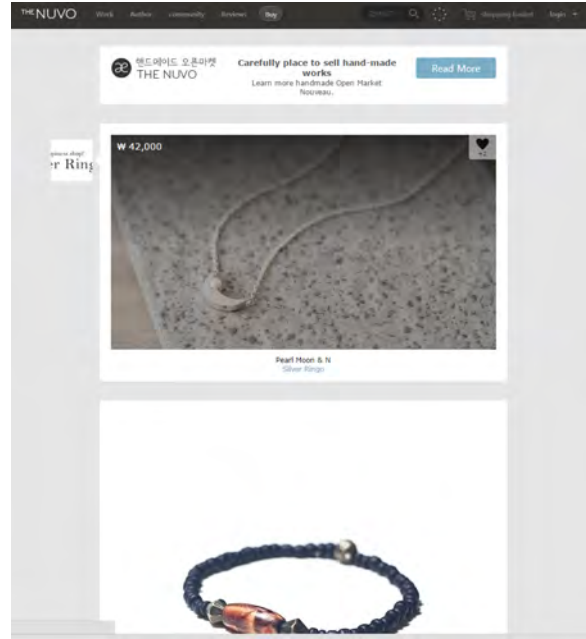
(sub) categories are sorted purely from the newest to the oldest. Exits from this main page product feed imply consumers either leave the site (like leaving a store) or shop in another set of categories. While it is feasible to consider shopping across all categories, the problem becomes substantially more complex with little attendant insight. In this regard, restricting our attention to one portion of the site is much like other research that focuses on a single category rather than a choice across a basket of goods. Exits and visits to other categories are captured via the outside good, and further discussion is included in the online Appendix A.1.

Product Display Ranking Algorithm   The products displayed to consumers are ordered using an algorithm determined by the platform, and the product list is updated daily using this algorithm (the site presents the same list to all consumers). While this algorithm is known to the researchers, it is not known to the sellers, and the consumers cannot distinguish between advertised and non-advertised listings. Key inputs to the algorithm include an item's (i) popularity score, (ii) slot adjustment score, (iii) days listed, and (iv) advertising score. The popularity score includes the cumulative total number of purchases, clicks, likes, comments, reviews, SMS shares, and seller activities. The popularity score is measured in cumulative (running) totals, so popular items ranked high are likely to acquire higher popularity scores via more exposures, clicks and likes. To offset this positive loop and to present more variety of items, the site applies a cumulative negative weight (slot adjustment score) to the items previously shown in top 30 positions. Further, to offset the effect that

older items acquiring higher popularity scores, the site applies a negative weight to the total number of days listed. Lastly, the advertising score mitigates the negative weighting on days listed, so older products can substantially increase their rank order in the listed items via advertising. The advertising advantage is attenuated as more sellers advertise, because the gains in position are offsetting.[14]

Figure 2:   Ranking Algorithm
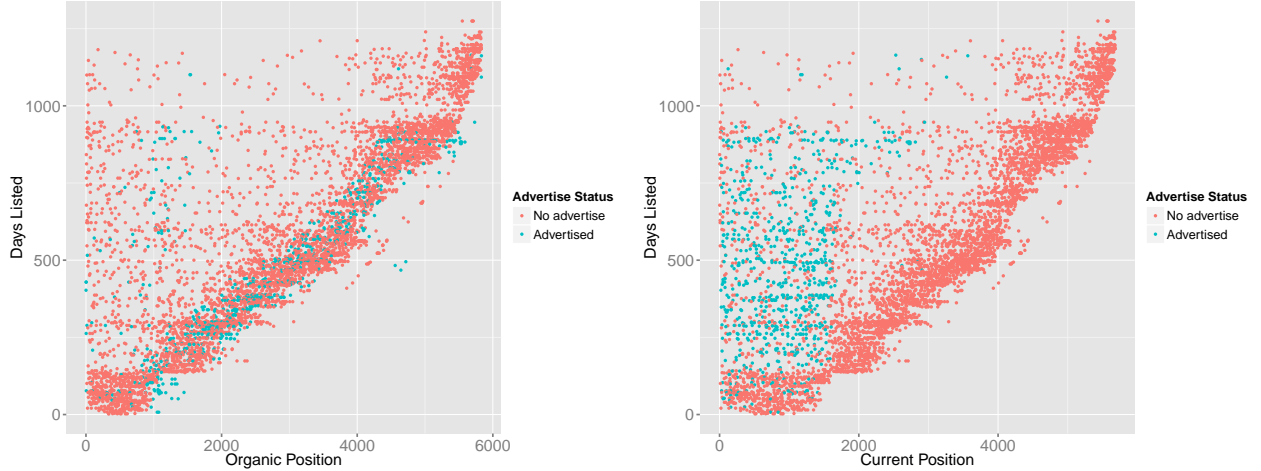
To visualize the role of advertising in determining a product's position on the site, the left side of Figure 2, plots each product's organic position in the absence of advertising score, against days listed. Each point represents an advertiser-product-day, and points marked in blue represent advertised goods. On the y-axis, smaller number means newer products, on the x-axis smaller number means higher in the display position. We find a strong relationship between the organic position and the days listed. Older products are pushed down to a lower rank making it harder for consumers to find them (note some older products attain higher position owing to higher popularity scores). On the right side, we plot each product's displayed position, and those that do advertise are moved to a upper position in the product feed. Contrasting the two plots, we see that the positions can improve substantially with advertising.

Advertising Fee Structure   The website imposes zero listing fees and 13% transaction fees (f^T). The platform also receives an additional 17% of the transaction price (f^A), if the product sold is an advertised product at the time of transaction. When listing an item, a seller has an option to opt-in for advertising and can change its advertising decision at any time. Currently the website does not impose fees based on clicks or impressions.

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[14]In the extreme case when every seller advertises, the resulting position will be the same as the organic position where no one advertises.

2.2 The Buyers

The buyer-side data include every visit, scroll, click, or purchase the website receives from its visitors. These data yield the number of times users visit the website, the products they search, the product detail pages they consider, and what items they purchase. Registration to the website is optional for the buyers, and non logged-in users are tracked by their cookie IDs.

2.2.1 Data Sample

The data are collected from mid May 2014 to mid Sep. 2015 and we focus our attention on the main page product feed. Of the 215507 users in this category, we focus on 254 with at least one purchase on this platform within the sample period. This approach is analogous to research using scanner data that filters customer based on a minimum number of category purchases (Guadagni and Little 1983, Gupta 1988).

We define a new visit (search session) if a user comes to the website for the first time, or after 24 hours of inactivity, or changes the product category, or continues to search after purchasing an item. Of the 1025 visits as we define, 117 sessions with a landing followed by an immediate visit to another area on the site were excluded.

Finally as the website imposes zero listing fees, many sellers do not unlist items when they become unavailable (e.g. temporarily sold out), instead sellers change the price to zero and mention in the product detail description that the product cannot be purchased. Hence, of the 72260 total searched, we exclude 543 with zero prices.

2.2.2 Buyer Side Statistics

Consumers make sequential decisions regarding visit, product search (impression), consideration (click), and purchase. Below we discuss each in the order of consumer decision process.

Visit (Search Session) We observe 251 individuals meeting our criteria, with a total of 908 visits. An individual makes 3.6 visits in average (median: 2 visits) during the sample period. These consumers search 71717 products in total, among which 764 are considered, and 38 are purchased within the main page product feed. Sample statistics appear to be consistent with the industry norm, taking into account that we are focusing on the individuals with purchasing history.[15]

Product Search and Consideration Summary statistics of consumer search and consideration behavior are presented in Table 1. The table indicates a mean level of 79 products searched,

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[15]The average conversion rate for an e-commerce website in Q1 2015 in the U.S. is around 2.53%, and internationally 2.32% (http://www.smartinsights.com/ecommerce/ecommerce-analytics/ecommerce-conversion-rates/). The conversion rate (#total demand/#total visits) in our sample is higher and is about 4.2%.

and 0.8 product detail page considered, but there is a large standard deviation associated with each. The cumulative distribution of each behavior is present in Figure 3. Consumers in our sample generally search extensively, and there exists significant heterogeneity in search across individuals. These consumers differ in length and depth of their search processes; Some search longer and consider only a few, whereas others search shorter and consider relatively many. All point to heterogeneity present in valuations and/or costs, and that consumers might possess consideration costs that are different from search costs.

Table 1:   Summary Statistics of Consumers Behavior

# Per Visit	Mean	Median	Std Dev	Min	Max
Search	79.0	20	283.5	7	4867
Consideration	0.8	0	3.1	0	44
Demand (Choice)	0.04	0	0.2	0	1
#Considerations/#Searches (%)	1.2	0	2.9	0	25
#Demand/#Considerations (%)	7.1	0	21.7	0	100

#Visits = 908, #Purchases = 38 (or about 4%)

Position Effect   In this sub-section, we draw attention to the importance of an integrated model of search, consideration and choice. Specifically we consider the role of position effects, as advertisers seek to obtain better positions in the product display list.

Figure 3:   Search Length, Consideration, Choice by Position
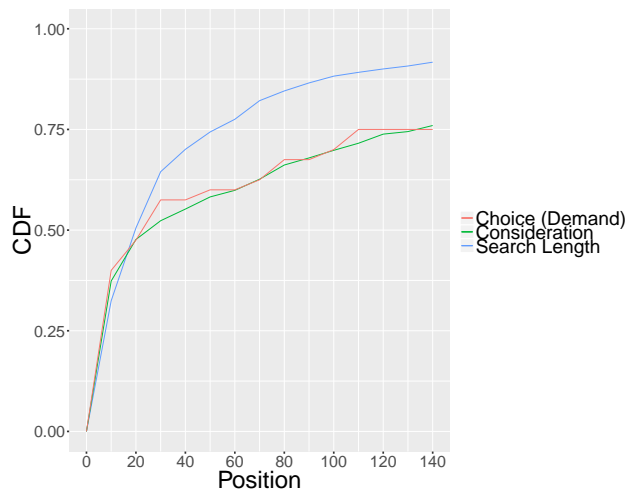
The product ranking and placement of advertised goods can have a considerable impact on items searched and considered. Such effect can be amplified for consumers with larger search and consideration costs. To explore this potential, Figure 3 displays how products placed in different positions are searched, considered and purchased. The product position in

the display list is plotted on the x-axis (bigger number means lower position in the display feed), and the cumulative probability of searches, considerations, choices attained by the position is plotted on the y-axis. The position effect is strongest for the search length, and the number of searches obtained decrease exponentially with position, similar to the findings in Ansari and Mela 2003.

However conditional on searching, the consideration likelihood does not exhibit an exponential decrease with the listing position, indicating that the magnitude of search costs and consideration costs may differ. This is shown on the left side of Figure 4, where product position is plotted on the x-axis and the probability of consideration conditional on searching is plotted on the y-axis. On the right side of Figure 4, the x-axis is again product position, and the y-axis represents the probability of purchase conditional on consideration. Here the decrease in choice with position is even smaller conditional on consideration, suggesting that preference plays bigger role at this decision stage relative to the sunk search and consideration costs.[16] These plots are consistent with our story that consumers first form a consideration set taking into account the preference and the costs of search and consideration, but then making a purchase decision at the end based on preference alone. In sum, all above findings suggest the desirability of explicitly modeling the choice (demand), as well as search and consideration costs separately.

Figure 4:   Position Effect on Consideration and Choice
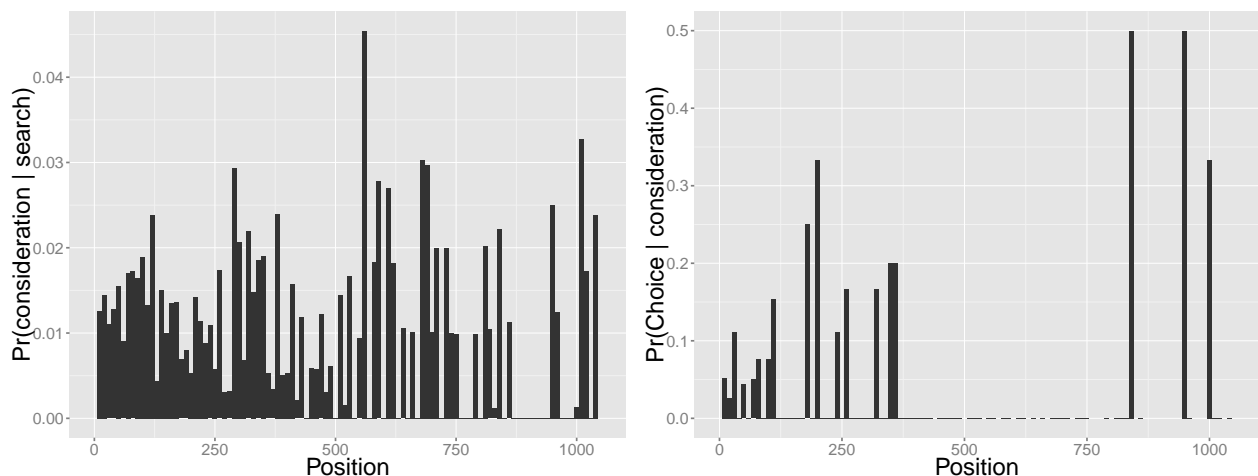
Top-Down Search Assumption   An important assumption in our search model is that consumers search products sequentially from top to bottom (scroll down the product feed). To explore this assumption, we count the total number of occurrences in which the consumers

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[16]Ursu 2015 also finds that conditional on a click, higher rank does not generate more purchases.

Table 2:   Deviations from Top-Down Search Process

Deviations in Searches	% of Visits
No Deviation	82.7%
1	13.8%
2	2.5%
3	0.7%
4	0.1%
5 or more	0.2%

Deviations in Considerations		% of Visits
# Considerations < 2		91.7%
#Considerations≥ 2	No Deviation	6.5%
	1 or more	1.8%

search or access product detail pages in the reverse rank order within each visit. In Table 2, we find that 83% of visits evidence search from top to bottom, and only few deviations occur in the consideration sequence.[17] When consumers deviate from the top-down search pattern, we presume the observed search and consideration sequences follow the order in which products are first encountered (that is, as exogenously determined by the firm's ranking algorithm).

2.3   The Advertisers

On the seller side, the site's log file includes advertisers' product listing, pricing and advertising decisions. These include details of listed items, when they are listed, and at what price. If sellers update their pricing and advertising decisions after the initial listing is created, these changes are also recorded.

2.3.1   Data Sample

The data are collected from mid May 2014 to mid Feb. 2016, but the key inputs to the ranking algorithm (popularity score, slot adjustment score) are only available after mid Nov. 2015. As such, we use the shorter span when estimating the advertiser model.[18] During this sample period, a total of 6235 products from 595 sellers were exposed to the consumers. On a given day on average, 5847 products were available and displayed as product feed, and 754 were advertised products. We omit products whose ranks are so low that they are never

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[17]Bronnenberg et al. 2016 provides supporting evidence (state dependence and a search funnel) for the existence of a sequential search process. In addition, top to bottom search behavior is well supported in the existing empirical literature (Granka et al. 2004, Ansari and Mela 2003), and can also be rationalized when consumers infer advertiser's quality from the position and search optimally (Chen and He 2011, Athey and Ellison 2011).

[18]Note that the buyer data interval used in estimation precedes supply side data interval, because we estimated the demand side prior to receiving supply side data. Buyer side data is now available till mid Feb 2016, and the demand estimation sample moments are qualitative similar to those that match the supply side estimation interval. For example, the summary statistics for searches are 78.1 (mean), 20 (median), 277.52 (std dev), 7 (min), and 4867 (max) respectively. As these moments are highly similar, parameter estimates are likely to be quite similar as well.

seen by the consumers even with advertising; excluding products whose positions are never above 3000 during our sample period yields a sample of 3466 products. We then restrict our sample to the product listings created after Mar. 2014 when the website went through a major renewal in its design and ranking algorithm. Lastly, we exclude products with zero prices and one product with an extreme price point ($6500), leaving us a final sample of 2853 products.

2.3.2 Supply Side Statistics

To obtain a better sense of seller listing strategies, we provide several summary statistics for the final sample of products ($N = 2853$).

Product Attributes Table 3 reports summary statistics of product attributes. The products have an average price of $14 with a large variation across products. The products also vary in their promotion percentage (discount %), number of likes and pictures.

Table 3:   Product Attributes

Attribute	Median	Mean	Std Dev	Min	Max
Listing Price ($)	14.0	19.5	23.3	0.1	430
Discount (%)	0	0.89	4.6	0	50.0
# Likes	1	1.6	2.2	0	31
# Pictures	4	3.6	1.7	0	27

Product Listing and Advertising Decisions A seller lists 9.3 items in average (median 4) with standard deviation of 16. Although there are a couple of sellers with more than 50 items, most are casual sellers with few listings. This implies that most sellers are sufficiently atomistic and none are likely to have undue influence on consumers, the platform, or other listing firms. (Figure 10 in online Appendix A.2.1)

35.8% of the sellers advertise at least one item, and advertised products constitute 19.5% of the total listed items. 76.5% of sellers adopt a simple binary strategy in their advertising decision in that they either list all their items as advertised products or vice versa (Table 4). Although sellers can change their advertising decisions at any time on the website, we find that these changes rarely occur, suggesting that sellers play a static, binary opt-in or opt-out strategy at the time of listing an item. The phenomenon is even more pronounced at the seller-item level. Only 1.1% of advertising decisions change across the products listed in our sample period (32 products from 7 sellers). As there is minimal longitudinal variation in advertising decisions, we aggregate data to the product level and treat advertising decision at the product level as an observation unit, instead of treating advertising decision at the product-day level as an observation unit.

Table 4:   Advertising Strategies

Pr(Advertise)	0	$0 < Pr < 1$	1	Total
# Sellers	197	72	38	307
# Products	2298	32	523	2853

Organic Strength and Advertising Decisions   To further illuminate the rationale underpinning sellers' advertising decisions, we compute products' "organic strength" as the mean residuals of the popularity score on days listed and feed position (see online Appendix C.2.1). In the absence of an advertising effect, a higher organic strength implies that a product is more likely to attain higher organic position in the search queue. In Figure 5, we consider the relationship between a listing's organic strength and the sellers' likelihood of advertising conditioned on that organic strength; organic strength percentile is plotted on the x-axis (bigger percentile means higher strength), and the percentage of products advertised within each bin is plotted on the y-axis. The figure shows that products who can organically appear early in the search order advertise less, suggesting strategic behavior on the part of the advertiser.

Figure 5:   Mean Organic Position and Advertising Percentage
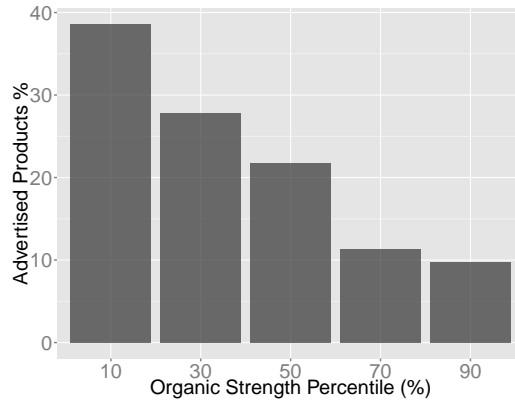
The observed pattern that organically highly ranked products advertise less than those organically ranked lowly suggests diminishing marginal returns to impressions (searches). To the extent that diminishing marginal returns exist, one might expect strategic sellers at the bottom of the queue to be more disposed to advertise in order to be bumped up into the range of searched goods and gain the first impressions, than those ranked nearer to the top who already have many impressions by virtue of their favorable ranking. In other words, the marginal benefit of being exposed via advertising is greater for those organically ranked low products. Hence, we accommodate diminishing marginal returns in our advertiser valuation

model.[19]

3   Model

In this section, we present a structural model encompassing the online marketplace. This model contains two components; i) a model of consumer search (impressions), selection of product detail pages (considerations or clicks), and purchases (choice); and ii) a model of sellers' advertising decisions wherein sellers compete for position in order to maximize their valuations from consumer search, consideration, and choice. Because the platform moves first by setting the rules of the advertising game (i.e. the ranking algorithm and the fee structure), the advertisers move second by responding to the rules of the game, and the consumers move last conditioned on platform and advertiser decisions, we solve the game via backward induction. Figure 6 depicts the agents and their interactions, as well as the respective sections that discuss how we model each agent's problem.

Figure 6:   Model Overview
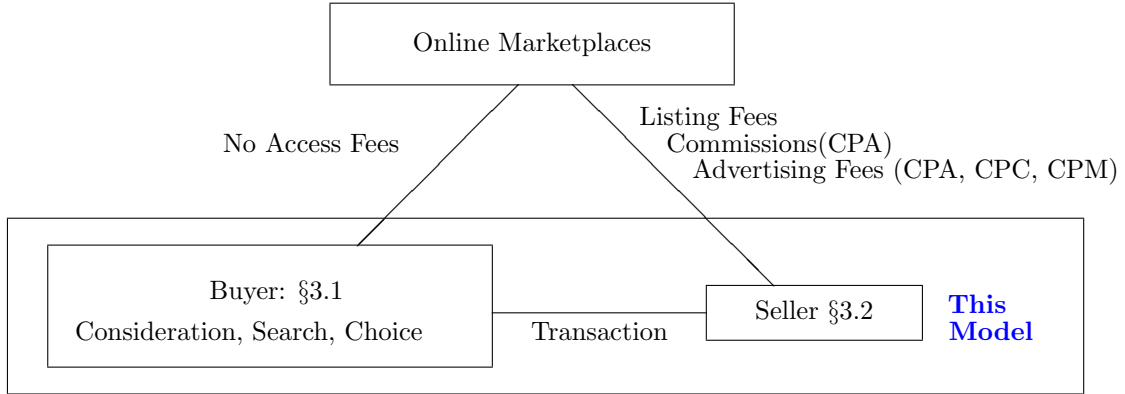
3.1   The Consumer Model

Figure 7 summarizes the series of conditional decisions described below.

1. **Visit** : A consumer first decides whether or not to visit the e-commerce website (start search session). We take consumer's visit decision as exogenously given; That is consumer's visit decision is independent of other consumers' behavior, sellers' advertising

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[19]In online Appendix A.2.2, we document some of the important observables that suggest different advertising valuations across products, and in A.2.3, we briefly discuss advertisers' pricing decisions. A key insight from this analysis is that advertising strategy appears independent of price, suggesting the plausibility of an exogenous pricing assumption.

Figure 7:   Consumer Model
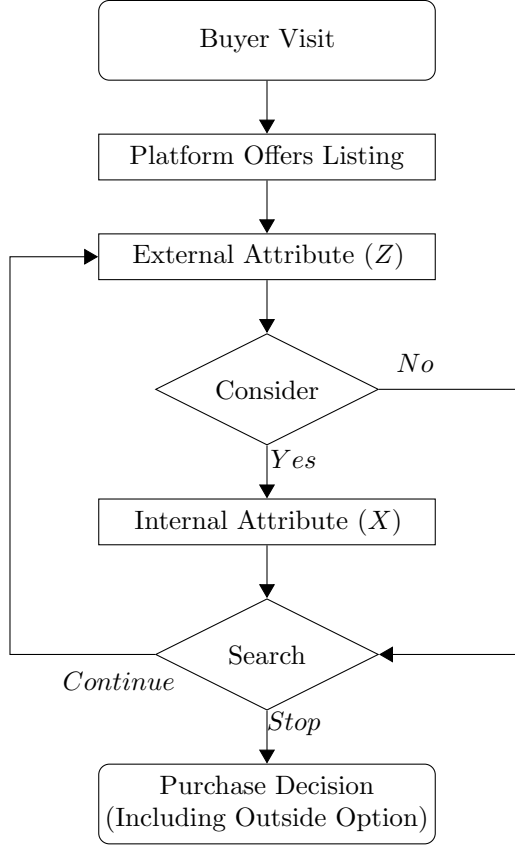
behavior, and the platform's ranking algorithm.[20]

2. **Product Search and Consideration** : Upon visiting the website, the consumer is presented an ordered list of items, one product at a time, where the arrival order of the products is exogenously determined by the platform's ranking algorithm. Faced with this list, a consumer can either click on a link to the first item's product detail page by incurring a consideration cost, or move to the next alternative on the list while incurring a search cost; that is we presume a sequential search process.[21][22] This leads

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[20]Like most scanner data papers, we focus on what happens conditional on store visit, and take shopping trip decision as given. With this simplifying assumption, we take the market size (consumer visits) to be fixed for the counterfactual exercises. One potential approach to relax this assumption is to model visit as a pre-search stage where a consumer makes a discrete decision based on the expected value (log inclusive value) of search, consideration, and purchase. Modeling visit decision adds an extra layer of computational complexity, but with relatively slim benefit of improving inferences for preference parameters.

[21]Online Appendix B.2 details how our model differs from Weitzman's model (Weitzman 1979), which has been the foundation for modeling sequential search in many papers (Kim et al. 2010, Koulayev 2013, Chen and Yao 2014). One major point of difference worth noting here is that the search order is exogenous as it is determined by the platform, whereas as in Weitzman's framework the consumer determines the order of search based on reservation utilities.

[22]Product ordering is affected by the aggregate consumers' behaviors and their impact on the popularity

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to the following sequence of steps:

- **1st Stage : Consideration (Product Detail Page Click) Decision**

  The consumer is presented with t-th positioned product (starting at $t = 1$), with some subset of the t-th item's attributes Z_t available on the product listing page (denoted "external" attributes). Having this partial information about the product's attributes, the consumer decides whether or not to add the t-th product into the consideration set by accessing (clicking) its product detail page. Once considered, the consumer gathers all information on the product detail page's "internal" attributes X_t (possibly correlated with the Z_t), and the matching value ϵ_t, and fully resolves any product uncertainty with regard to its utility. Once the consideration decision is made, the consumer decides whether to search the $(t + 1)$th position product. See Section 3.1.2.

- **2nd Stage : Search or Exit Decision**

  Conditioned on the information obtained in searching so far (the set $\{\mathbf{Z}_1, \mathbf{Z}_2, ..., \mathbf{Z}_t, \delta_1 \cdot (\mathbf{X}_1, \epsilon_1), \delta_2 \cdot (\mathbf{X}_2, \epsilon_2), ..., \delta_t \cdot (\mathbf{X}_t, \epsilon_t)\}$, where $\delta_t = 1$ if an item is considered in step t, else 0), the consumer decides whether or not to continue search for the $(t + 1)$th product. If the consumer decides to continue search, partial information on $(t+1)$th product is revealed, $\mathbf{Z}_{t+1}$, the consumer incurs a search cost, and the consumer moves to the 1st stage of $(t + 1)$th step. If the consumer decides not to continue, the entire search process terminates. See Section 3.1.3.

3. **Choice (Purchase)**

   Once the search process terminates, the consumer has a final consideration set that consists of the items whose product detail pages have been visited (clicked) and the outside option. The consumer rationally chooses the highest utility alternative among the ones considered. See Section 3.1.1.

We explicate each step of the purchase funnel - first the utility function related to choice (purchase) is specified, then consideration and search decisions are explained.

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scores raising endogeneity concerns. We address this by endogenizing how consumers form beliefs about the product attribute transition using the empirical distribution of current product ordering. This ordering is based on popularity scores, sellers' advertising decisions and platform's ranking algorithm (see online Appendix B.1). In policy simulation, these transition beliefs are updated to account for the changes in either the platform's ranking algorithm or the aggregate consumers' behaviors with respect to the changes in sellers' advertising decisions (online Appendix C.2.3).

3.1.1 Choice

Let consumer i's indirect utility from purchasing a product j be

$$u_{ij} = \mathbf{X}_j \alpha + \mathbf{Z}_j \beta + \epsilon_{ij}$$

$$u_{i0} = \epsilon_{i0} \tag{1}$$

where $\{\mathbf{X}_j, \mathbf{Z}_j\}$ are row vectors of product attributes. ϵ_{ij}s follow $N(0, \sigma_\epsilon^2)$ and these are iid across consumers and products. When a consumer searches through the product list, some product characteristics are accessible without retrieving the product detail page, and these external attributes presented on the product listing page are defined as $\mathbf{Z}_j$. Other product attributes revealed inside the product detail page (which is accessed after clicking on an item in the product listing page) are denoted as $\mathbf{X}_j$. The last term ϵ_{ij} captures consumer i's idiosyncratic taste about product j, and this match value is also inferred together with $\mathbf{X}_j$ when the product is considered. For example, a consumer looking for a handmade item finds a product from certain brand ($\mathbf{Z}_j$) on a product listing page, clicks the link and considers its product detail page, then finds that it is not adorned with a particular gemstone ($\mathbf{X}_j$) though he likes the design detail (ϵ_{ij}). Consumers do not know the specific values of $\{\mathbf{X}_j, \epsilon_{ij}\}$ before accessing the product detail page, but they know the distribution of $\{\mathbf{X}_j, \epsilon_{ij}\}$ conditional on the information in hand $\{\mathbf{Z}_j\}$. This conditioning becomes material when there is a correlation between the external attributes ($\mathbf{Z}_j$) and the internal attributes ($\mathbf{X}_j$), enabling consumers to better forecast the attributes on the detail page (in the extreme case of a perfect correlation, the $\{\mathbf{X}_j\}$ provide no additional information and the only uncertainty is given by the $\{\epsilon_{ij}\}$. The outside good (not purchasing) does not require a search, and is available in the consideration set from the beginning at no cost.

The consumer's choice probability conditional on the consideration set Γ_i is

$$Pr(d_i^p = j \mid \Gamma_i \,; \theta^p = \{\alpha, \beta\}) = Pr(u_{ij} \geq u_{ij'} \ \forall j \neq j', \ j, j' \in \Gamma_i)$$

where superscript p stands for purchase (choice), d_i^p indicates whether item j is chosen by consumer i, and Γ_i contains the outside option value and the products whose product detail pages have been accessed. As there is a selection issue, ϵ_{ij}s do not follow iid $N(0, \sigma_\epsilon^2)$ conditional on the consideration set.[23]

3.1.2 Consideration

Consideration involves clicking an item to review its product detail page and adding it to one's consideration set. This is a necessary step prior to purchase. Considering a product

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[23]For example, if a consumer considers and draws high ϵ_{ij}s in the beginning of the search process, this consumer will terminate search early, and the ϵ_{ij}s included in the consideration set will be truncated below. Similar discussion on this selection issue can be found in Chen and Yao 2014 and Honka 2013.

detail page does not afford any current period utility though it is costly; rather, the benefit from considering accrues in future periods via adding an item to a consideration set for choice. As $\{\mathbf{X}_j, \epsilon_{ij}\}$ are not known prior to considering the detail page, the decision to consider involves a trade-off between the cost of considering and the likelihood that the considered product's utility will be higher than any other item currently in the consideration set. Stated differently, consumers will consider if the expected benefit of doing so exceeds the costs.

Consideration Costs We proceed under the assumption that consideration costs are constant and specify the cost of consideration, c^c as

$$c^c = exp(\gamma_1)$$

Because there is no immediate period benefit from considering, the current period payoff of consideration decision, U^c, is given by its costs,

$$U^c_{d^c ij(t)} = \begin{cases} \eta^c_{0ij(t)} & \text{if not consider, } d^c = 0 \\ -c^c + \eta^c_{1ij(t)} & \text{if consider, } d^c = 1 \end{cases}$$

where $j(t)$ represents product j encountered by consumer at position t, and $\eta^c_{d^c ij(t)}$ is assumed to follow iid Type I Extreme Value (Gumbel) distribution. The alternative-specific shock can be interpreted as a classic structural error term related to consideration preference that is known to the consumer, but not observed by the researcher. It may also include unobservable preference shock related to product $j(t)$ that is known to the consumer before making the consideration decision. This error term is distinguished from the match value $\epsilon_{ij(t)}$, which is revealed inside product detail page after considering.[24]

Consideration Benefits Recall, the benefit from visiting a product detail page accrues in future periods via its addition to the consideration set. Given that the utility of this item is not fully revealed until consideration, the consumer makes the consideration decision based on beliefs about whether adding current item to the consideration set will yield higher utility than previously considered items. The maximal utility, u^*_{it}, among the products in the consideration set Γ_{it} can be expressed as

$$u^*_{it} = \begin{cases} \max \left\{ u_{ij(t)}, u^*_{it-1} \right\} & \text{if } j(t) \in \Gamma_{it} \\ u^*_{it-1} & \text{if } j(t) \notin \Gamma_{it} \end{cases}$$

where $j(t)$ represents product j encountered by consumer at position t. In other words, if there is no additional consideration, there can be no increase in the maximum utility in the consideration set. The outside good option of not purchasing is included in the consideration

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[24]A similar discussion on the difference between the match value term and the classic structural error term can also be found in footnote 24 Honka 2013.

set from the beginning, so $u_{i0}^* = u_{i0}$. Using this notation, the conditional value function of the consideration decision is given by the sum of the current period utility ($-c^c$ if consider, and 0 if not consider) and the future utility flows accruing from the consideration decision, net of the choice specific error $\eta_{d^c it}^c$, that is:

$$v_0^c(u_{it-1}^*, \mathbf{Z}_{j(t)}) = \int_{u_{it}^*} Emax^{search}\left(u_{it}^*, \mathbf{Z}_{j(t)}\right) f_0^c\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) \tag{2}$$

$$v_1^c(u_{it-1}^*, \mathbf{Z}_{j(t)}) = -c^c + \int_{u_{it}^*} Emax^{search}\left(u_{it}^*, \mathbf{Z}_{j(t)}\right) f_1^c\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right)$$

where the future utility flows after the consideration step are given by the option value of recommencing search (see Figure 7), or

$$Emax^{search}\left(u_{it}^*, \mathbf{Z}_{j(t)}\right) = E_{\eta_0, \eta_1}\left[\max\left\{v_0^s\left(u_{it}^*, \mathbf{Z}_{j(t)}\right) + \eta_{0it}^s, \; v_1^s\left(u_{it}^*, \mathbf{Z}_{j(t)}\right) + \eta_{1it}^s\right\}\right]$$

$$= ln\left[exp\left(v_0^s\left(u_{it}^*, \mathbf{Z}_{j(t)}\right)\right) + exp\left(v_1^s\left(u_{it}^*, \mathbf{Z}_{j(t)}\right)\right)\right] + \kappa \tag{3}$$

where κ is the Euler constant, and v_0^s, v_1^s are conditional value functions of the search decision, which are later defined in equation (6).

The first line in equation (2) captures the value of not considering, v_0^c, and the second line captures the value of considering, v_1^c. f_0^c and f_1^c are the state transitions for consumers' beliefs about the future highest utility achievable, u^*, based on current state, u_{it-1}^*, in the consideration set and the partial attributes $\mathbf{Z}_{j(t)}$ presented at position t on the product listing page (online Appendix B.1 derives the state transitions, f^c, on these beliefs).

$Emax^{search}\left(u_{it}^*, \mathbf{Z}_{j(t)}\right)$ represents the expected value of search (which immediately follows the consideration decision per Figure 7). This expectation is taken over the search stage alternative-specific shocks, η_{it}^ss, as they are not observed at the time of consideration (that is, they are revealed to the consumer in the subsequent search step). In other words, the $Emax^{search}$ function represents the future value of consideration because it represents the option value of the search step that follows the consideration step. Under the logit error assumption, this is the inclusive value of the search decision. We don't specify discount factor in front of the future values, as the time interval between consideration and search decision is short.

Consideration Decision   Given the choice specific value functions above, the conditional choice probability of no consider, $d^c = 0$, can be expressed as

$$p_0^c\left(u_{it-1}^*, \mathbf{Z}_{j(t)}\right) = \frac{1}{1 + exp\left(v_1^c\left(u_{it-1}^*, \mathbf{Z}_{j(t)}\right) - v_0^c\left(u_{it-1}^*, \mathbf{Z}_{j(t)}\right)\right)} \tag{4}$$

This is the popular dynamic logit model where the choice probabilities depend on differences in choice specific value functions (Aguirregabiria and Mira 2010, Arcidiacono and Miller 2011). Once the consideration decision is made at position t, a consumer proceeds to search

decision, and decides whether they want to terminate or continue to search $(t+1)$th item.

3.1.3 Search

Analogous to consideration, consumers will search when the benefit of doing so exceeds the cost. With the normal distribution assumption on the match value, ϵ_{ij}, the expected increase in future u^* from continuing search decreases, as the maximum utility in the consideration set in hand, u^*, increases. Under the assumption of constant consideration and search costs, this is a sufficient condition for the optimal stopping rule, as the probability of continuing search decreases with respect to u^*.

Search Costs Analogous to consideration, we assume constant search costs c^s and specify it as

$$c^s = exp\left(\gamma_2\right)$$

Search Benefits Once u_{it}^* is revealed based on the consideration decision ($u_{it}^* = u_{it-1}^*$ if t-th position product is not considered), the consumer must then decide whether or not to search the $(t+1)$th product in order to obtain information about the $\mathbf{Z}_{j(t+1)}$ (see Figure 7). The current period payoff of sequential search decision is

$$U_{d^s it}^s = \begin{cases} u_{it}^* + \eta_{0it}^s & \text{if search is stopped, } d^s = 0 \\ -c^s + \eta_{1it}^s & \text{if search is continued, } d^s = 1 \end{cases} \tag{5}$$

where $\eta_{d^s it}^s$ is assumed to follow iid Type I Extreme Value (Gumbel) distribution. The first line in equation (5) indicates that a consumer who stops search at step t will receive utility u_{it}^* (reflective of the best alternative found prior to stopping search) plus a random shock observed by the consumer but not the researcher. This alternative-specific shock might include unobserved factors such as internet connectivity, sudden incoming online messages from a friend, or general time constraints that affect search behavior. Alternatively, if a consumer continues search, he will pay a search cost now, but accrues no benefit until after the entire search process is completed. This benefit represents the expected future value arising from potentially finding a better alternative to add to the consideration set and purchase by continuing search. The conditional value function for the search decision at position t, that is the sum of the current period utility ($-c^s$ if search is continued, and u_{it}^* if search is stopped) and the future utility flows accruing from the search decision, net of the search choice specific error $\eta_{d^s it}^s$, can be written as

$$v_0^s(u_{it}^*, \mathbf{Z}_{j(t)}) = u_{it}^*$$
$$v_1^s(u_{it}^*, \mathbf{Z}_{j(t)}) = -c^s + \int_{\mathbf{Z}_{j(t+1)}} Emax^{consider}\left(u_{it}^*, \mathbf{Z}_{j(t+1)}\right) f_1^s\left(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}\right) \tag{6}$$

where

$$Emax^{consider}\left(u_{it}^{*}, \mathbf{Z}_{j(t+1)}\right) = E\left[\max\left\{v_{0}^{c}\left(u_{it}^{*}, \mathbf{Z}_{j(t+1)}\right) + \eta_{0i(t+1)}^{c}, \; v_{1}^{c}\left(u_{it}^{*}, \mathbf{Z}_{j(t+1)}\right) + \eta_{1i(t+1)}^{c}\right\}\right]$$

$$= ln\left(exp\left(v_{0}^{c}\left(u_{it}^{*}, \mathbf{Z}_{j(t+1)}\right)\right) + exp\left(v_{1}^{c}\left(u_{it}^{*}, \mathbf{Z}_{j(t+1)}\right)\right)\right) + \kappa \qquad (7)$$

$f_{1}^{s}\left(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}\right)$ is the distribution of consumers' beliefs on future $\mathbf{Z}_{j(t+1)}$ conditional on the decision to continue search (see online Appendix B.1). The continuation value of search is given in the second line of equation (6), and corresponds to the expected maximum of the utility of the ensuing consideration decision, as the continuation of search affords the option of potentially adding another item to the consideration set. This expected future value is given in equation (7). The discount factor is again assumed to be 1, as the time interval between search decision and following consideration decision for $(t+1)$th product is short. Though we discuss state transitions in online Appendix B.1, it is worth noting that the search decision can be informative about consideration if the attributes on the product listing page $\mathbf{Z}_{t}$, are correlated with the attributes inside the product detail page $\mathbf{X}_{t}$.

Search Decision With the double exponential parametric assumption on $\eta_{d^{s}it}^{s}$, the conditional choice probability of ending search, $d^{s} = 0$, is given by

$$p_{0}^{s}\left(u_{it}^{*}, \mathbf{Z}_{j(t)}\right) = \frac{1}{1 + exp\left(v_{1}^{s}\left(u_{it}^{*}, \mathbf{Z}_{j(t)}\right) - v_{0}^{s}\left(u_{it}^{*}, \mathbf{Z}_{j(t)}\right)\right)} \qquad (8)$$

Note that *stop searching* is a terminal decision that ends the search process all together. If we denote *stop searching* position as $t = T^{s}$, the consumer's optimal purchasing decision is to choose the alternative (including the outside option of not purchasing) that delivers the highest utility $u_{iT^{s}}^{*}$ within the consideration set $\Gamma_{iT^{s}}$. This payoff related to purchase is embedded in the search decision as we model $v_{0T^{s}}^{s} = u_{iT^{s}}^{*}$.

3.2 The Advertiser Model

Upon deciding to list an item on the platform, sellers are faced with the decision of whether or not to advertise. Advertising on the site has two offsetting consequences. On the positive side, advertised goods are listed in more favorable position, thereby increasing exposures and potentially clicks and purchases, which in turn increases advertiser revenue. On the negative side, sellers pay fees for advertising. We presume that sellers advertise if the expected valuation gains from advertising surpass the expected cost of advertising. This expected valuation gains depend on i) how advertising affects *consumer choice, consideration, and search*, ii) the *competition for advertised slots* as improving an advertised product's position necessarily entails lowering those of other products, and iii) the *cost of advertising* arising from fees charged by the platform. As the solution to the advertiser problem requires firms to form beliefs about consumer response, product position, the cost of advertising, and

competitive landscape, we detail these points in sub-section 3.2.1 before formalizing the advertiser problem in sub-section 3.2.2.

3.2.1 Key Assumptions

The advertiser problem conditions upon the consumer behavior, competitor behavior, and the platform's behavior in terms of fee structure and ranking algorithm. We detail our assumptions pertaining to each.

Consumer Behavior We assume that sellers form rational expectations about demand, consideration and search based on their beliefs about increase in product placement via advertising, and that strategic interactions (competitive effects) work through the changes in product placement. Specifically, given the belief on product position from the advertising strategy, the seller is assumed to form rational beliefs on consumer demand, consideration, and search responses based on the distribution of consumer preferences and costs from consumer model:

$$\widehat{D_{j,d_j^a \mathbf{d^a_{-j}}}} = D \left(\widehat{Rank_{j,d_j^a} \mathbf{d^a_{-j}}}, \mathbf{X}, \mathbf{Z} \right); \ \widehat{C_{j,d_j^a \mathbf{d^a_{-j}}}} = C \left(\widehat{Rank_{j,d_j^a} \mathbf{d^a_{-j}}}, \mathbf{X}, \mathbf{Z} \right); \ \widehat{I_{j,d_j^a \mathbf{d^a_{-j}}}} = I \left(\widehat{Rank_{j,d_j^a} \mathbf{d^a_{-j}}}, \mathbf{X}, \mathbf{Z} \right)$$

(9)

where $\widehat{Rank_{j,d_j^a} \mathbf{d^a_{-j}}}$ is the belief on product j's position when the competing advertising strategies are given by $\mathbf{d}^a_{-j}$, which is a vector of beliefs regarding competing advertiser advertising decisions.

Competitive Behavior Consistent with the patterns observed in the data, we presume that the seller's advertising decision is a binary discrete choice at the product level. That is, the seller opts-in for advertising when listing an item if it is profitable to do so, and competes for better placement. This problem comports to a simultaneous entry game of incomplete information, wherein the potential entrant faces uncertainty about others' valuations and thus advertising decisions (e.g., Berry and Reiss 2007, Seim 2006, Sweeting 2009). Following the prior research, we employ a "semi-reduced form" specification of firms' valuations, and strategic interactions enter through consumer demand, consideration, search responses via changes in product placement. This specification is detailed in Section 3.2.2.

We presume that sellers form bounded rational beliefs about others' advertising decisions. Under the rational expectations assumption, solving optimal advertising decision in our context of an online marketplace requires forming beliefs about many thousands of other sellers' (products') advertising strategies. This is not only computationally intractable due to curse of dimensionality, but also implies that small firms (who carry a median of 4 products in our data) know the valuations of thousands of other small firms; this assumption

strikes as implausible given the effort such a task would entail. Moreover, in the limit, an advertiser's rank does not explicitly depend on what other specific firms do, but instead the aggregate number of firms that advertise. Accordingly, we assume that each seller (product) is sufficiently atomistic that each seller (product) conditions on the advertising probability distribution moments (aggregate states) rather than each other seller's actual advertising probability (individual states) when forming beliefs about their own ranking. Finally, we presume that the aggregate beliefs are consistent with the underlying advertisers' decisions at equilibrium. For example, we presume an advertiser's beliefs about the expected number of competing advertisers is simply the sum of individual advertising decisions across competing firms.[25]

Platform Behavior We consider two aspects of platform behavior; search rankings wherein the platform determines the order of items presented to consumers, and the fees charged to sellers. While the cost of advertising could involve a variety of potential pricing mechanisms available to the platform (fixed-fee-per-ad-slot, auction-mechanism-per-ad-slot, cost-per-click, cost-per-mille, and/or cost-per-action), our inference regarding the advertiser model reflects the institutional details of our setting wherein the e-commerce platform charges a percentage commission as advertising fees based on sales. We will further incorporate cost-per-click and cost-per-mille in the advertiser model as part of our policy simulations.

3.2.2 Valuations

A seller k chooses an optimal advertising strategy for product j as defined by an indicator variable d_j^a ($d_j^a = 1$ advertises, $d_j^a = 0$ does not). We model sellers as gaining valuations from three sources: (i) choice (demand), (ii) consideration (click), and (iii) search (impression). Impressions and considerations can generate value from, for example, enhancing the likelihood of webrooming and creating value via branding.[26] Specifically, seller k's valuation for product j from advertising decision d_j^a is

$$\pi_{jkd^a} = \theta \cdot \mathbf{w}_{jk} \cdot \mathbf{1}(d^a = 1) + \pi_{jd^a}^D + \pi_{jd^a}^C + \pi_{jd^a}^I$$

where $\pi_{jd^a}^D$, $\pi_{jd^a}^C$, $\pi_{jd^a}^I$ are valuations from choice (demand), consideration (click), search (impression) respectively. To accommodate product-seller level heterogeneity and to control for the remaining effect of observable characteristics on advertising beyond what consumer

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[25]Our approach is inspired by the oblivious equilibrium (Weintraub et al. 2005) and the approximate aggregation in Krusell and Smith 1998 and Lee and Wolpin 2006, but we consider a static environment. Recently this method has also been adopted in analyzing ad exchange auctions. (Iyer et al. 2014, Balseiro et al. 2015, Lu and Yang 2016)

[26]Chan and Park 2015 also distinguish valuations from probability of browsing, clicking, and the click being the terminal click separately in the sponsored search advertising context.

purchase funnel predicts (e.g. non-refundable products tend to advertise less. See online Appendix A.2.2), $\mathbf{w}_{jk}$ is introduced as an additive term. To estimate the model, we impose an iid structural error term ξ_j, and assume that the seller advertises product j if doing so is profitable, that is if the below condition is satisfied.

$$\left(\theta \cdot \mathbf{w}_{jk} + \pi_{j1}^D + \pi_{j1}^C + \pi_{j1}^I\right) + \xi_j \geq \left(\pi_{j0}^D + \pi_{j0}^C + \pi_{j0}^I\right)$$
$$\xi_j \sim N(0, \sigma_\xi^2) \tag{10}$$

Valuations from Choice (Demand)   The first component of the advertiser's valuation comes from profit earned when a product is sold on the website. The sale of a product accrues revenue, and at the same time, the seller pays a fixed transaction fee as a percentage of the transaction amount, f^T. In addition, the seller also pays an additional fixed percentage as a commission, f^A, when the product is advertised and sold. The valuation from choice (demand) is represented as

$$\pi_{jd^a}^D = \theta^D (1 - f^T - f^A \mathbf{1}(d_j^a = 1) - \delta) D_{jd^a} p_j \tag{11}$$

where D_{jd^a} and p_j are demand and price for product j respectively.[27]

δ is a term capturing the marginal cost, as well as the cannibalization effect wherein the seller loses the chance to sell the item without fees on their own or other sites. For two products with the same marginal costs, the higher δ value means that the seller gains less value from a sale made on this website. Selling on the platform means potentially losing the same sale from the same consumer in other channels where the fees are lower (e.g. own individual websites or blogs). For the same marginal costs, higher δ implies that the seller has a greater incentive to redirect consumer to the outside channels for purchase and to encourage consumer web-rooming.

Valuations from Consideration (Click) and Search (Impression)   The other two components of the advertiser's valuation come from consideration (click) and search (impression). The seller gains benefit from considerations and searches made by the consumer, but the seller also pays potential cost-per-click (CPC) fees, f^C (a fixed fee per click made by the consumer), and/or potential cost-per-mille (CPM) fees, f^I (a fixed fee per thousand impressions delivered to the consumer). These potential fees are charged to the sellers regardless of whether an item is sold on the website (recall a consumer must click on an item for it to enter the consideration set for potential subsequent sale). These valuations reflect the standard concept that exposures and clicks have advertising value to the seller over and above an immediate

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[27]In online Appendix A.2.3, we show that seller pricing is not correlated with the advertising decision. Because products are usually sold via multiple sales channels, it is plausible that the advertising strategy on this web platform is independent of the pricing decision set for all sales channels. Hence, we treat price as exogenous (which also has the benefit of substantially simplifying the supply side analysis).

sale, either through branding or future sales.[28]

We assume that the seller's valuation from considerations and searches exhibit diminishing marginal returns. This assumption is motivated by the findings in our data (see sub-section 2.3.2) and the widely used practice of "frequency capping" in display advertising market. Many experts believe that repeated exposures past a certain threshold will not increase conversion rate or brand equity, thus the number of impressions served needs to be capped to avoid over exposure. The valuation from considerations and searches are given by

$$\pi_{jd^a}^C = \theta^C log\left(C_{jd^a}\right) - f^C C_{jd^a} \tag{12}$$

$$\pi_{jd^a}^I = \theta^I log\left(I_{jd^a}\right) - f^I I_{jd^a}$$

where C_{jd^a} and I_{jd^a} are considerations and searches (in thousands) respectively.

Advertiser Decision Given the underlying parameters of the model $\left(\theta,\ \delta,\ \theta^D,\ \theta^C,\ \theta^I\right)$, and with the parametric assumption on ξ_j, the probability of advertising in equilibrium is given by

$$p_{jk1}^a = \Phi\left[\frac{\left(\theta\cdot\mathbf{w}_{jk} + \pi_{j1}^D + \pi_{j1}^C + \pi_{j1}^I\right) - \left(\pi_{j0}^D + \pi_{j0}^C + \pi_{j0}^I\right)}{\sigma_\xi}\right] \tag{13}$$

4 Estimation

4.1 The Consumer Model

4.1.1 Consumer Utility

We specify consumer i's utility from purchasing product j from category-seller k to be

$$u_{ijk} = \mu_k - \beta_p log(P_j) + \beta_z Z_j + \alpha X_j + \epsilon_{ij}$$

$$u_{i0} = \epsilon_{i0}.$$

The information depicted on the product listing page and known to consumers before consideration includes seller identity, price and the number of likes, $(\mu_k,\ P_j,\ Z_j)$. The number of pictures X_j, and the match value ϵ_{ij}, are revealed inside the product detail page.

We abstract away from product level unobservables μ_j, and include category-seller level fixed effects μ_k, to capture preferences for certain categories and brands. Many products that are searched have zero demand and zero considerations in our data, making it difficult to recover product level unobservables. Second, seller level unobservables capture unobserved vertical differentiation in this market, where authorship and craftsmanship creates uniqueness and distinguishable features at the seller level. Products nested within seller share these

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[28]In online Appendix (Section A.2.2) we show that firms who include a link to their own websites tend to advertise more, a finding suggestive of greater valuations for those who can more readily redirect exposed customers to their own sites and avoid paying cost-per-action (CPA) fees to the platform.

unobservables.[29]

4.1.2 Likelihood and Heterogeneity

The log-likelihood of consideration, search and purchase is denoted as

$$L(\Theta_1) = L(\alpha^{\mathbf{g}}, \beta^{\mathbf{g}}, \gamma_1^{\mathbf{g}}, \gamma_2^{\mathbf{g}}, \lambda^{\mathbf{g}}) \quad g = 1, ...G$$

where $\lambda^1, ..., \lambda^G$ represent the type probability of each segment when there are G latent classes (Heckman and Singer 1984, Kamakura and Russell 1989).

Let T_i^s reference the position where individual i chooses to stop searching such that $d_{iT_i^s}^s = 0$. The likelihood of observing $\mathbf{d}_i = \{d_{i1}^c, ..., d_{iT_i^s}^c, d_{i1}^s, ..., d_{iT_i^s}^s, d_{i1}^p, ..., d_{iT_i^s}^p\}$ for individual i in latent class g is defined as

$$L_i(\Theta_1^g) = \int_{u_{iT_i^s}^*} ... \int_{u_{i1}^*} \int_{u_{i0}^*} f^u(u_{i0}^*) \, \mathcal{L}(\mathbf{d}_i \mid u_{i0}^*, ..., u_{iT_i^s}^*, \mathbf{Z}, \mathbf{X}; \Theta_1^g)$$

$$= \int_{u_{iT_i^s}^*} ... \int_{u_{i1}^*} \int_{u_{i0}^*} f^u(u_{i0}^*) \prod_{t=1}^{T_i^s} \mathcal{L}_t^{consider} \mathcal{L}_t^{search} \mathcal{L}_t^{purchase}$$

where the initial probability $f^u(u_{i0}^*)$ is the distribution of outside option value $f^u(\epsilon_{i0}) = \phi(\epsilon_{i0})$, and superscripts c, s, and p represent consideration, search and purchase (choice) respectively. The information used to infer the consumer primitives comes from these three observed decisions, and the log-likelihood of the sample data can be written as

$$L(\Theta_1) = \sum_{i=1}^{I} ln \left(\sum_{g=1}^{G} \lambda^g L_i(\Theta_1^g) \right) \tag{14}$$

where we integrate out latent class consumer heterogeneity. In online Appendix C.1.1, we derive the joint likelihood of consideration, search and purchase.

4.1.3 Solving the Dynamic Problem

We estimate the consumer model as an infinite horizon problem, using MLE in the outer loop (parameter estimation) and value function iteration for the inner loop (future value terms and resulting choice probabilities conditioned on those parameters). Further detail can be found in online Appendix C.1.2.

4.1.4 Identification

Heterogeneity in search costs cannot, in general, be separately identified from vertically and horizontally heterogeneous tastes, without the help of observed demographic characteristics or panel data (Hortaçsu and Syverson 2004, Moraga-Gonzalez et al. 2010, Sorensen 2001). In

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[29]The inclusion of category-seller level unobservables and exclusion of product level unobservables is motivated by data limitation, and not from the functional form restrictions required for identification. In estimation, we add a category dummy for accessories (e.g. necklace, ring, bracelet) and a dummy for large sellers (brands with more than 150 product listings).

our empirical application, most consumers' visits are highly episodic (with median 2 visits per individual), thus we develop our discussion based on cross-sectional observations.

In Weitzman's sequential search models, the non-linearity in the reservation utility equation helps to identify the impact of heterogeneity in the effects of any "observed" covariate on valuation separately from its impact on the search costs, under the parametric distributional assumption on heterogeneity such as normal distribution assumption in Kim et al. 2010 and Chen and Yao 2014. Any exclusion restriction that affects only one side, either valuation or search costs, yields stronger identification. For example slot position will not likely affect consumers' valuation of a good. In an analogous vein, the preference parameters in our model are separately identified from the search costs under the finite mixture parametric assumption, using the variation in when consumers stop searching with regards to the variation in product characteristics they face. The consideration cost is separately identified from the search cost as we benefit from having both the (i) search data (when consumers stop searching) as well as (ii) consideration data (which products they consider within the search span). Therefore in theory, search and consideration data alone are sufficient to identify all parameters in our finite mixture model.

Besides non-linearity and parametric distributional assumption, identifiability of heterogeneity in "observed" covariates is strengthened with additional information on choices (purchase) arising from the same underlying preferences and search costs. This is because conditional on items searched or considered, the final choices are not affected by search or consideration costs, yielding another exclusion restriction which improves inferences on estimates (see Chen and Yao 2014 and Kim et al. 2015). Online Appendix C.1.3, reports the results from a simulation exercise showing that the inclusion of purchase data significantly reduces the standard errors of the parameter estimates, especially for the preference parameters, over search/consideration data alone.

Unobserved heterogeneity, for example the variance in the preference error terms and the variance in search/consideration costs error terms, cannot be separately identified. Thus parametric assumptions are imposed on these "unobserved" terms with normalized scales. These include specifying the structural error terms associated with search ($\eta^s_{d^s it}$) and consideration ($\eta^c_{d^c it}$) to follow iid Type I Extreme Value (Gumbel) distribution with scale 1, and the variance of match value to be $\sigma^2_\epsilon = 1$. A separate error term is introduced for each stage ($\eta^s_{d^s it}, \eta^c_{d^c it}$), and adding a structural error term that is unknown prior to entering a particular stage (search, consideration) enables the closed form value functions reported in equations (3) and (7), which greatly reduces the computational complexity. It is plausible that the alternative-specific shock that affects whether or not a consumer wants to continue

search is different from the shock that affects whether or not the consumer wants to click a certain item.[30]

4.2 The Advertiser Model

4.2.1 Constructing Advertisers' Beliefs

As the platform's ranking algorithm and the underlying scores are not shared with the sellers, they must form beliefs regarding their relative product rank with and without advertising in order to assess the attendant impact on impressions, considerations and purchase. Following the discussion in sub-section 3.2.1, we assume that each seller (product) is sufficiently atomistic, and forms bounded rational beliefs about others' advertising decisions in predicting own product rank. Specifically we assume that advertisers' beliefs on the product placement for a given day t depend on its own advertising strategy d_j^a, the *aggregate states* of others' advertising strategies $E_t(\mathbf{d}_{-j}^a)$, the total number of products available J_t, and own product j's attributes that affect the rank score.

$$\widehat{Rank}_{j,t,d_j^a,\mathbf{d}_{-j}^a} = g\left(d_j^a,\, E_t(\mathbf{d}_{-j}^a),\, J_t,\, \text{Days Listed}_{jt},\, \text{Organic Strength}_j\right) \qquad (15)$$

where "organic strength" is the mean residuals of the popularity score on days listed and product position. We specify the function $g(\cdot)$ to be a generalized additive model (see online Appendix C.2.1).[31] Note that the effect of competition manifests via $E(\mathbf{d}_{-j}^a)$. As competing firms advertise more, one's own rank (and thus impressions, considerations and sales) decreases. Because each advertiser faces a similar problem, to find the equilibrium behavior we solve each advertiser's respective problem conditioned on $E(\mathbf{d}_{-j}^a)$, recompute $E(\mathbf{d}_{-j}^a)$ using these collective decisions, and iterate until convergence for policy simulations (for more detail, see sub-section 4.2.3 and online Appendix C.2.3).

In addition to beliefs about competing firms' behaviors, advertisers form beliefs about consumer behavior as well. Equipped with beliefs about their own product placement in the search queue, $\widehat{Rank}_{j,t,d_j^a,\mathbf{d}_{-j}^a}$, sellers form beliefs about consumer behavior in terms of demand, consideration, and search responses (equation (9)).[32] As we formulate the advertiser model in a static framework, expected impressions, considerations and demand are imputed over the duration of the product listing. Using the consumer demand model, consumer responses are

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[30]See Seiler 2013 p.183 for a similar discussion, where separate set of error terms are introduced for each decision stage in order to obtain an analytic solution for the value functions.

[31]To validate this assumption, we show that the actual ranking by the platform's algorithm and the approximate ranking based on equation (15) yield similar predictions even though the latter assumes smaller information demands on the part of the advertiser (Figure 11 in online Appendix C.2.1)

[32]Formally speaking, the seller's expectation requires integrating out over the belief distribution of product ranks. In order to reduce the computational cost, seller's beliefs are predicated instead on the expected value $\widehat{Rank}_{j,t,d_j^a,\mathbf{d}_{-j}^a}$.

simulated for each day based on sellers' product position beliefs $\widehat{Rank_{j,t,d_j^a},\mathbf{d}_{-j}^a}$, and aggregated across time periods.

4.2.2 Likelihood

The advertising model parameters are $\Theta_2 = \left(\theta, \theta^D, \theta^C, \theta^I, \delta\right)$. The likelihood of observing seller k's advertising decision on product j, d_{jk}^a, is given by

$$\mathcal{L}_{jk}^a(d_{jk}^a; \Theta_2) = {p_{jk1}^a}^{1(d_{jk}^a=1)} \times \left[1 - p_{jk1}^a\right]^{1(d_{jk}^a=0)}$$

where p_{jk1}^a is the advertising probability defined in equation (13). Further, the log-likelihood of the sample data for the advertiser probit model is given by

$$L^a(\Theta_2) = \sum_{j=1}^{J} ln\left(\mathcal{L}_{jk}^a(d_{jk}^a; \Theta_2)\right) \tag{16}$$

4.2.3 Solving the Advertiser Problem

We estimate the advertiser model in three stages. In stage 1, we estimate the function governing sellers' beliefs on product rank, equation (15). In stage 2, sellers' beliefs on product placement and consumer responses with respect to advertising are constructed. By contrasting the valuation from demand, consideration and search responses when advertising and when not advertising, the seller's advertising probability is imputed. The parameters in interest, $\Theta_2 = \left(\theta, \theta^D, \theta^C, \theta^I, \delta\right)$, are then recovered in stage 3 using maximum likelihood estimation method based on the likelihood function in equation (16). In online Appendix C.2.2, we describe these estimation stages in detail and discuss how the equilibrium advertising strategies are computed for the policy simulation.

4.2.4 Identification

As in the standard probit model, the variance of the structural error term is normalized to $\sigma_\xi = 1$. Under the functional specification assumed on the advertiser model, the advertiser valuations for demand, considerations, and searches are identified from the observed likelihood of advertising with respect to variation in rank and resulting changes in consumer responses due to advertising. More specifically, rewriting the difference in seller k's valuation for product j from opting-in and opting-out of advertising yields:

$$\begin{aligned}
\pi_{jk1} - \pi_{jk0} = {}& \theta \cdot \mathbf{w}_{jk} + \theta^D(1 - f^T - \delta)p_j\left(D_{j1} - D_{j0}\right) \\
& + \theta^C\left(log\left(C_{j1}\right) - log\left(C_{j0}\right)\right) - f^C\left(C_{j1} - C_{j0}\right) \\
& + \theta^I\left(log\left(I_{j1}\right) - log\left(I_{j0}\right)\right) - f^I\left(I_{j1} - I_{j0}\right) \\
& - \theta^D f^A p_j D_{j1}
\end{aligned} \tag{17}$$

Note that in our empirical setting, the sellers pay advertising fees only when opting-in for

advertising and when the sales are realized. Thus the valuation from demand, θ^D, can be identified from the sensitivity of advertising decision with respect to the variation in expected advertising commissions incurred ($f^A p_j D_{j1}$). Second, the valuations from considerations and impressions are recovered from the increase in considerations and impressions via advertising. If an increase in considerations (impressions) is correlated with advertising, valuations will be positive. Finally, δ is identified from the revenue increase due to advertising. Given θ^D, if firms are less likely to advertise when there is an increase in demand, this implies a higher δ.

5   Results

This section reports the estimates from the consumer and advertiser models.

5.1   The Consumer Model

Table 5 presents the consumer model results. The first column reports the parameter estimates of the homogeneous model. Estimates from the preference utility model indicate that the price (an external attribute) and the number of pictures (an internal attribute) affect consumers' preferences, and thus consumers' search, consideration and purchase behaviors.[33] Both the search and consideration costs significantly affect the length and the depth of search and the formation of the consideration set. The magnitude of consideration cost is about 9 times that of the search cost.

The second column in Table 5 reports the results from a two segment model where the heterogeneity is imposed on both preference and cost, and the third and the fourth columns report results from the model with two and three segments where the heterogeneity is imposed only on the cost parameters. The three-segment model with heterogeneity on the cost parameters yields the best result in terms of the Bayesian information criterion (BIC).[34] About 77% of the consumers belong to the group with the search cost estimate of 0.174 and the consideration cost estimate of 1.708. About 16.2% of the consumers search less (with higher search cost), but consider considerably more (with much lower consideration cost), and about 6.5% of the consumers search and consider more than the other segments. In-sample model fit is reported in Table 13 in online Appendix.

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[33]Owing to the craft nature of these goods, price is likely endogenous with respect to quality. While we control for this by adding category-seller fixed effects, we conjecture that the true price elasticity may be higher than indicated in the table. Nonetheless, we do not believe this will bias our other estimates or the results of the advertising-oriented counterfactual simulations in Section 6.

[34]The BIC of the four segment model is 17616.

Table 5:　　The Consumer Model Estimates

	Parameter	1 Segment	2 Segments	2 Segments on costs	3 Segments on costs
Preference					
Type1	# Pictures (X)	**0.215** (0.101)	0.153 (0.145)	**0.200** (0.098)	**0.194** (0.098)
	Log (Price) (Z)	$-$**0.236** (0.136)	-0.073 (0.212)	$-$**0.238**(0.138)	$-$**0.248**(0.138)
	# Likes (Z)	-0.002 (0.005)	-0.000 (0.006)	-0.003(0.005)	-0.003(0.005)
	Constant	$-$**2.404** (0.505)	$-$**2.54** (0.758)	$-$**2.222**(0.502)	$-$**2.107**(0.502)
Type2	# Pictures (X)		**0.239** (0.136)		
	Log (Price) (Z)		-0.386 (0.198)		
	# Likes (Z)		-0.016 (0.019)		
	Constant		$-$**1.759** (0.718)		
Cost					
Type1	Consideration	**1.518** (0.008)	**1.479** (0.014)	**1.479** (0.014)	**1.200** (0.024)
	Search	**0.164** (0.0004)	**0.180** (0.001)	**0.180** (0.001)	**0.187** (0.004)
Type2	Consideration		**1.545** (0.012)	**1.545** (0.012)	**1.581** (0.015)
	Search		**0.153** (0.001)	**0.153** (0.001)	**0.152** (0.001)
Type3	Consideration				**1.708** (0.053)
	Search				**0.174** (0.002)
Type Prob					
	Pr(Type1)		**0.918** (0.013)	**0.917** (0.013)	**0.162** (0.044)
	Pr(Type2)				**0.065** (0.011)
LL	$(N = 71547)$	-9271.04	-8831.13	-8832.78	-8740.24
BIC		18609	17807.9	17766.4	17614.9

5.2　The Advertiser Model

Table 6 details the estimates from the advertiser model. Via taking log on consideration and search, this specification allows for diminishing marginal returns as discussed in Section 2.3. Additionally, a number of covariates control for various product types' observed differences in advertising rates apart from their impact on consumers' search, consideration and demand responses. For example, consumers' behavior is not found to be responsive to different materials the products are made out of, conditional on price information (and other variables entering the consumer model). However the sellers systematically advertise stone-made products more frequently in our data, which suggests that the competition might be more intense with this type of products.

Of note, advertisers in this online marketplace face negative valuations from demand, owing to high commissions from transactions and advertising (f^T, f^A) and the high value for δ, which captures the marginal cost as well as the the foregone value of selling the item without (with lower) fees on their own or other sites (76% of the transaction amount). As

Table 6:   The Advertiser Model Estimates

	Parameter	Estimates
δ	Cannibalization	**0.76** (0.078)
θ^D	Demand	0.52 (0.410)
θ^C	log(Considerations+1)	**0.006** (0.001)
θ_1^I	log(Searches (in thousand))	0.000 (0.000)
θ	Constant	**−0.98** (0.056)
	Brand Group 1 (# product listing > 150)	**−1.66** (0.160)
	Brand Group 2 (85 <# product listing≤ 150)	**−0.38** (0.060)
	Include URL	**0.27** (0.063)
	Silver	**0.43** (0.153)
	Stone	**0.19** (0.087)
	Bracelet	**0.28** (0.068)
	Refundable	**0.26** (0.059)
	LL ($N = 2853$)	−1263.8

Note: Cannibalization (δ) includes marginal cost

Negative valuation from demand if advertised: $(1 - f^T - f^A - \delta) = -0.06$

the commissions from transaction and advertising constitute a large portion of the cost, with $f^T + f^A = 17\% + 13\% = 30\%$, the resulting valuation from demand is negative when sellers advertise $(100 - 17\% - 13\% - 76\% = -6\%$ of the transaction amount). This loss presumably motivates sellers to redirect consumers' purchases to outside channels (to their own websites or stores) to avoid paying high commissions on sales or promote buyers' web-rooming behavior.

To assess when the valuations from clicks are highest, Figure 8 plots the increase in logged considerations from advertising on the y-axis and the number of logged considerations conditioned on not advertising on the x-axis (holding others' advertising decisions fixed). Each dot represents a listed product in the data. The color of the dots indicates the valuation per consideration calculated based on the estimate θ^C and adjusted to be in dollar metric. The shape of the dots indicates the observed advertising decisions in the data, where the squares (rounds) represent currently "non-advertising" ("advertising") products. The product observations with close to zero considerations in the absence of advertising have higher valuations from a unit increase in consideration (darker color dots), and are more likely advertise. In other words, the first few considerations generate the largest valuations to advertisers. The quantiles for average value per consideration are $0.04 (25%), $0.13 (50%), $0.48 (75%). The average conversion rate (#total demand/#total considerations) in our data is 5%, so the cost per conversion is calculated to be $2.6. As the median price is $14,

Figure 8:　　　Valuations from Consideration

Avg value per consideration quantiles: $0.04 (25%), $0.13 (50%), $0.48 (75%)
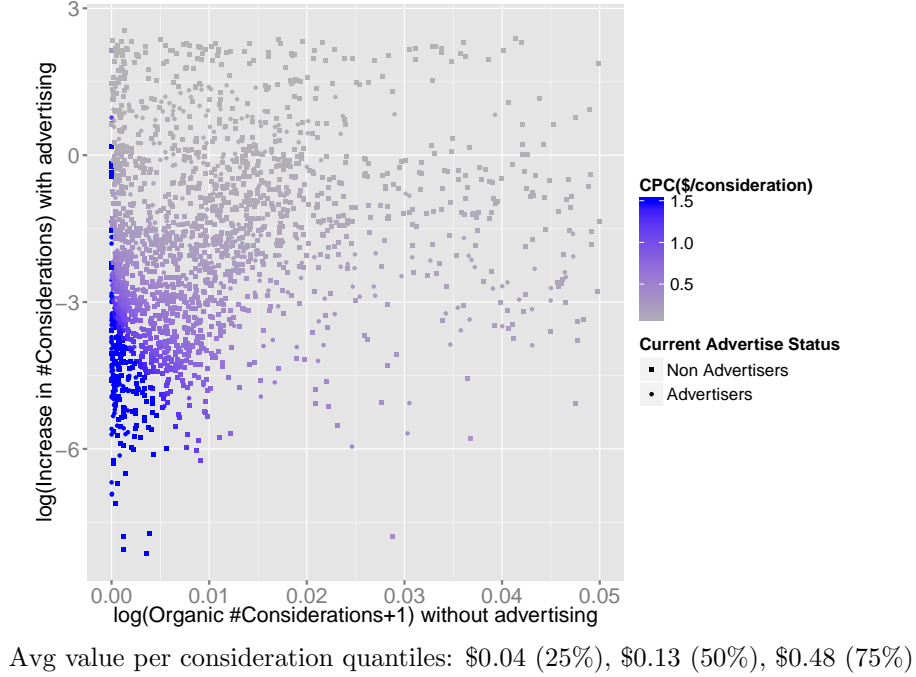
the total willingness to pay for considerations is about 18.6% of the transaction amount.[35] On the other hand, we find that advertisers rarely gain valuations from searches (exposures), which is consistent with the findings in Chan and Park 2015, where the values per effective impression and non-terminal click are found to be all zero in the context of a leading search engine firm in Korea.

6　Policy Simulation

Owing to the structural underpinning of the models of consumer and advertiser behavior, it is possible to explore options by which the platform can improve its revenue and/or welfare of consumers and advertisers. On the consumer side, these questions include (i) the trade-off between listing consumers' favored items first versus disrupting that order via the insertion of advertised goods, and (ii) which content should be placed on the product listing page versus product detail page. In order to be concise, we focus upon the first question in this paper. On the supply side, we explore (i) changes in the ranking algorithm, and (ii) the fee structure of the online marketplace. We detail these policy analyses below.

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[35]Related, in keyword sponsored search context, Yao and Mela 2011 estimates the mean value of a click to be $0.25 for software products with typical retail price of $22, and our consideration valuation is consistent with their findings.

6.1 Consumer Model Simulations

6.1.1 Ranking Algorithm - Effect on Consumer Search, Consideration, Demand

The placement of advertised products has indirect effects on consumer behavior via reducing search and consideration costs. From the platform's perspective, therefore, an important question lies in measuring the trade-off between placing an organic product of consumer's best interest against an advertised product that collects additional fees. Featuring advertised products generates advertising revenue, but at the same time may impede the search process. This can reduce sales and the resulting transaction commissions. Hence, we contrast the current ranking scheme with one that orders products by the highest mean utility across users in order to measure the attendant revenue implications on the demand side. For each given day, the available (listed) products are sorted by the choice utility (consumption utility) in equation (1) based on the consumer model estimates.[36]

Findings suggest that the current ranking algorithm (which includes favorable listings for advertised goods) generates higher platform profits than a counterfactual ranking algorithm that favors goods of higher utility. More specifically, ranking goods by utility decreases consumers' search costs (consideration costs) by 1.2% (2.0%) because they find their preferred items earlier and consider fewer items. Figure 9 plots the product position of the purchased item on the x-axis against the cumulative density of purchases realized on the y-axis. Under the counterfactual ranking, the product is purchased much higher in the search queue (earlier in the search process) relative to the current ranking algorithm. Likewise, the number of items sold increases by 125% and consumers' choice utility (consumption utility) increases by 179%.

However somewhat surprisingly, though beneficial for consumers, reordering items by utility decreases platform's and sellers' revenue by 52.9% and 49% respectively. In our empirical setting, this result is mainly driven by the fact that consumers are price sensitive (items in consumers' best interests are usually low priced items), and the increase in sales volume is not large enough to offset the decrease in total revenue or the transaction commissions.[37] Accordingly, our analysis provides one insight regarding why many online marketplaces collect advertising fees and do not display items purely organically, or do not sort items from the lowest price to the highest as a default display.

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[36]As the consumer model preference parameters in our empirical context are estimated to be from one segment, this sorting leads to a single product display ranking across consumers. Thus we do not consider rankings customized to individual consumer.

[37]The actual loss in revenue will be even greater, if the platform does not collect advertising fees under the best utility scheme.

Figure 9:   Demand Response: Sorting Listing Positions by Consumer Utility
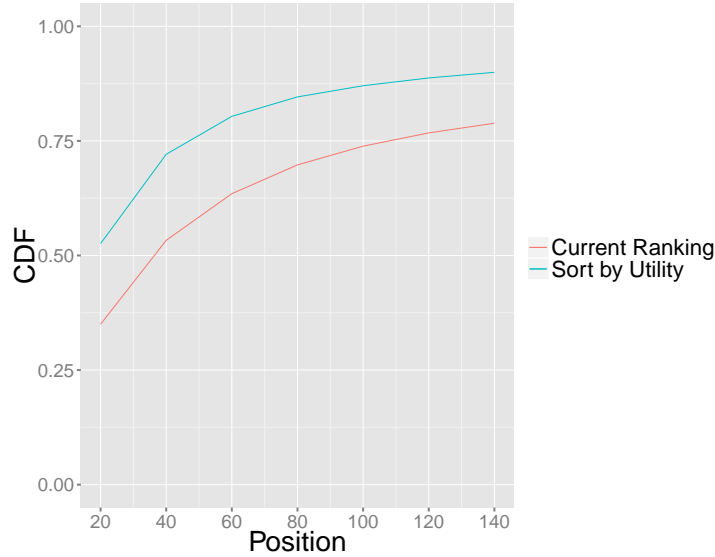
6.2 Advertiser Model Simulations

6.2.1 Ranking Algorithm - Effect on Advertising Strategies

While featuring advertised products makes search less efficient, thereby reducing sales, it incentivizes firms to increase their advertising and obtain better placement. Hence, there is a trade-off between the consumer side and the advertiser side of the platform. Amplifying the advertising effect in a counterfactual analysis enables us to assess how this trade-off affects consumer welfare, advertising competition, and ultimately the platform's profits.

Specifically, we consider the case where the position of an advertised product is improved by 10% (which converts to about median increase in 200 slots) over the current policy (by adjusting the weight in the ranking algorithm). This manipulation sharpens the trade-off between the two sides of the platform by providing a greater incentive to advertise. As the ranking algorithm changes, sellers' beliefs on their own and others' product positions will also change. Thus, we construct sellers' counterfactual beliefs per equation (15) under the new ranking algorithm. This construction ensures that sellers' beliefs on aggregate states (mean advertising probability) are consistent with the underlying advertisers' decisions in equilibrium (see online Appendix C.2.2 for detail). In other words, the increased incentive to advertise is offset to some degree by the competitive response of other sellers who are also likely to increase their advertising, thus mitigating the rank increase from advertising in the absence of such response.

Consistent with our predictions, the mean advertising probability increases from 19.5% to

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21.7%. On the consumer side however, consumers' search lengths, considerations, and choices decrease by 0.5%, 0.02%, and 6.6% respectively, and their ex-post consumption utility lessens by 8.3%. This negative effect on consumer's welfare can be explained by the finding that organically weaker (less popular) products have higher marginal valuation for advertising, and more prone to advertise. In this regard, heavier weight on advertising disrupts consumers' search processes as the likelihood of finding goods they want (popular products) within their search lengths decreases.

Contrasting the two effects, we find the effect of increased advertising revenue offsets the loss in transaction revenue on the consumer side and that the platform's profit increases by 12.3% due to this increase in commissions from advertising. In contrast, sellers' overall welfare decreases by 2.6% as they face higher advertising competition and pay more for advertising commissions.

6.3 Advertising Fees

As various fee structures differentially affect each stage of the purchase funnel, a question of general interest is which pricing mechanism should be used by the online marketplace platform. Hence, we explore the implication of a fixed cost-per-click (CPC) basis, and a percentage of the sale basis (cost-per-action or CPA) in next counterfactual analysis.[38]

6.3.1 Cost per Action

We first vary the advertising commission on transaction (f^A, currently 17%) (columns 1 and 2 in Table 7). This analysis indicates that, although setting a higher advertising commission ($f^A = 30\%$) increases platform's profits by 7% by collecting more fees from advertisers, higher commissions reduces the probability of advertising by 6.1% and sellers' welfare by 2.9%.

In contrast, lowering advertising commission to ($f^A = 10\%$) increases the sellers' advertising probability and sellers' welfare by 5.1% and 0.3% respectively, but reduces the platform's profits by 7%. Hence, there is a trade-off between the advertisers' and the sellers' welfares, and the fee structure plays an important role in determining the share of the "valuation pie" when fees are based on cost-per-action.

6.3.2 Cost per Click

In the third column of Table 7, the CPA from the advertising is set to be zero ($f^A = 0$) and the CPC is set at the median value for consideration estimated from our advertiser model ($f'_C = \$0.13$). We find that, even though sellers' profits decrease with the fees to be paid to

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[38]As sellers in our empirical context rarely gain valuations from searches (exposures) and thus CPM, we focus our attention on CPA (purchase) and CPC (consideration) while setting CPM (cost-per-mille) f^I to be zero.

Table 7: Fee Structure

% Changes	Seller Profits	Seller Welfare	Prob (ad)	Platform Profits
Higher ad commission: $f_T = 13\%, f'_A = 30\%$	−3.3	−2.9	−6.1	7.0
Lower ad commission: $f_T = 13\%, f'_A = 10\%$	0.8	0.2	5.1	−7
Remove ad commission: $f_T = 13\%, f'_A = 0$ Raising CPC: $f'_C = \$0.13$	−19.4	9.6	−2.9	75.5
Remove CPA: $f'_T = 0, f'_A = 0$ Raising CPC: $f'_C = \$0.35$	−40	2.8	−11.2	156

the platform, sellers gain in overall welfare as they now do not face negative valuation on demand when advertising $(1 - f_T - f'_A - \delta = 1 - 0.13 - 0 - 0.76 = 0.11 > 0)$.

6.3.3 Combining CPC and CPA

To find the (pareto) optimal fee structure for this online marketplace platform, we conducted a coarse grid search combined with a steepest descent method on the profit objective function as a function of fees. The result yields a fee structure that leads to the highest profits for the platform, under the participation constraint that sellers retain at least the current overall welfare level at equilibrium.[39]

Findings are presented in the fourth column of Table 7. The optimal cost-per-action (CPA) fees are zero $(f_T = 0, f'_A = 0)$ coupled with a more substantial $0.35 charge for the considerations (CPC).[40] Although sellers' profits from transactions on this platform decrease under the optimal fee structure, sellers gain positive valuations presumably from potential future sales or additional demand directed toward their own websites via consumers' web-rooming behaviors. Reducing CPA, and instead charging advertising fees based on CPC (and/or CPM) has the potential for pareto improvement leading to positive profit outcomes for both sellers and the platform.

7   Conclusion

This paper considers the role of "shelf space allocation" in the context of online marketplaces. To achieve this aim, we consider all three agents in the two-sided network; i) the platform who

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[39]During the iteration process, we impose sellers' participation constraint that each seller's utility is greater than the minimum of the seller utilities estimated in actual fee structure setting. Those who gain lower than this threshold are assumed to dropout (unlist items).

[40]Although in a different context, our result is consistent with the average CPC ($0.35) for Facebook Advertising in Korea (http://www.rudibedy.com/blog/facebook-advertising-cpc-cpm-per-country/)

sets the advertising fees and designs the website in regards to information structure (whether to present attributes on the search page or the consideration page) and placement of items listed on the market, ii) the sellers who make advertising decisions conditioned on platform's policies and expected consumer behavior, iii) consumers who search, consider and make purchase decisions given the preferences, search/consideration costs, information structure and ranking algorithm. We build a model that coherently encompass consumer behaviors and the advertising decisions. Owing to the rapid growth of these platforms, insights into the nature of consumer search, consideration and purchase as well as advertiser behavior can lead to economically consequential improvements in platform behavior.

This research offers a number of advances with regard to the prior literature pertaining to two-sided markets in online environments. On the consumer side, our approach extends prior research that focuses on search to integrate multiple aspects of the purchase funnel, including search, consideration and choice. On the seller side, we model the strategic interactions of advertisers in the context of limited online shelf space. Specifically, we consider how advertisers react when fees are used to apportion space available in online marketplaces, and link these fees to the stage of the consumer purchase funnel. An integrated view of the role of advertising on the purchase funnel is necessary to determine how to best monetize advertiser valuations. For example, high CPA based commissions coupled with no listing fees incentivize advertisers to encourage "webroom"; that is to list items on a marketplace site in the hopes they (the advertiser) do not sell, but instead generate traffic via clicks or exposures to the advertisers' own site where there are no commissions to be paid.

On the consumer side, we find that the information on price (external attribute) and the number of pictures (internal attribute), and both the consideration and search costs affect the length of search, formation of consideration set, and ultimately the products purchased by the consumers. The consideration cost is estimated to be about 9 times larger than the search cost, and there exists considerable heterogeneity in search and consideration costs across consumers.

In the model of seller valuations, we find the combined marginal cost as well as the lost chance of selling the item without fees on their own or other sites, is substantial (76% of the selling price). As a result, the valuation from unit demand is negative (-6% of the transaction amount) for the sellers who advertise. This negative valuation incentivizes sellers' redirecting consumers, and provides one seller side explanation for the widespread web-rooming phenomenon. The median valuation from consideration (click) is estimated to be $0.13, and sellers rarely gain positive valuations for impressions above and beyond the value for considerations and immediate sales. Finally, we find evidence of diminishing

marginal returns for considerations and searches, consistent with the industry practice of "frequency capping".

From the perspective of the platform, different scenarios in ranking advertised products and setting advertising fee structure are considered through policy simulations. We find that listing advertised goods favorably generates higher platform profits than listing consumers' highest utility items first, predominantly because consumers prefer low priced items. In other words, advertising enables sellers to exploit search inefficiencies. Further the platform is better off by lowering the cost-per-action (CPA, that is the commissions on sales) which will soften cannibalization (negative valuation from demand) and mitigate the web-rooming effect (wherein sellers hope consumers who see items listed on the platform instead buy them on the sellers' or others' sites). Reducing CPA, and instead charging advertising fees based on CPC (and/or CPM) has the potential for pareto improvement, wherein both advertisers' welfare and the platform's profits increase.

Although this paper investigates broad range of interactions among buyers, sellers and the platform in an e-commerce platform, a number of additional extensions are possible. First on the buyer side, one can extend our model to incorporate consumer's site visit incidence decision that can depend on which sellers advertise and how platform ranks advertised versus organic products. Another possible extension is to consider cross category and cross store search, consideration, and choice which will yield some novel insights on platform's strategies, and a future research is warranted.

Second, sellers' pricing behavior is taken as given in our policy simulation, and we do not consider competition between e-commerce platforms. We believe this is a reasonable assumption in our empirical application where price is not found to be correlated with advertising decision and the varying fee structure of other platforms. Nonetheless, marketing implications of multi-homing in a two-sided online marketplaces where cross promotion and advertising can produce potential benefits are yet unexplored in the literature and represent an important direction for future analysis.

Third, our focus is upon online merchandising platforms. The search model can also be applied to blogs and social media websites where visitors search a list of article titles (and possibly the first line of the content and the main picture) from top to bottom sequence and decide which ones to consider/read further. The search model is also suitable to the growing mobile-commerce environment, where only one or two products are visible on a screen and consumers scroll down in top to bottom fashion while deciding which ones to gather further information along the searching process. Presumably, the advertiser model could be applied to these contexts as well. Given the relatively nascent state of empirical research on online

transactional platforms, we hope that our work will serve as a useful step in this rapidly growing context.

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Online Appendix

A Data

A.1 The Buyers: Data Sample

The transactional site we consider has several "categories" including (i) a main landing page product feed with all variety of goods, (ii) more specialized categories such as jewelry and handbag, and (iii) various designer stores (brand stores). Hence, the considered site bears similarities to a retailer (such as a grocer or a department store) with many categories. We focus our attention on the main landing page category with the reasons discussed in sub-section 2.1.1, but provide some summary statistics for the entire platform across categories in this sub-section. Focusing on the individuals with purchasing history, Table 8 presents the shares by (sub) categories. Main landing page category constitutes the largest share of search sessions and searches, and the second largest share of considerations and purchases.

Table 8: Shares of Search Sessions, Searches, Considerations and Purchases

Top Categories	% Search Sessions	% Searches	% Considerations	% Purchases
Main Page	18.9	21.8	12.5	12.3
Jewelry	7.4	9.8	6.5	5.8
Bracelet	5.8	16.0	13.4	9.1
Brand1	3.7	5.3	8.0	14.9
Clothes/Acc.	3.0	2.0	1.3	0.3
Brand2	2.5	2.4	4.3	10.0
Necklace	2.5	4.2	4.1	2.9
Ring	2.3	3.1	4.4	1.6
Brand3	2.0	3.4	2.4	3.9

A.2 The Advertisers

A.2.1 Product Listing and Advertising Decisions

Figure 10 portrays the concentration of goods across sellers, the x-axis is the seller ID and the y-axis is the number of products per seller. Most merchants are casual sellers with few listings (median 4), and there are only a couple of sellers with more than 50 items. We find our results to be robust to the exclusion of these large sellers. Overall, the non-concentrated nature of sellers suggests that each is sufficiently atomistic as to have little, if any, marginal impact on the observed advertising equilibrium outcomes.

A.2.2 Advertising Decisions

Table 9 documents some observable aspects that suggest different valuations across products via a logit regression analysis of the products' advertising status against independent variables,

Figure 10:   Product Listings
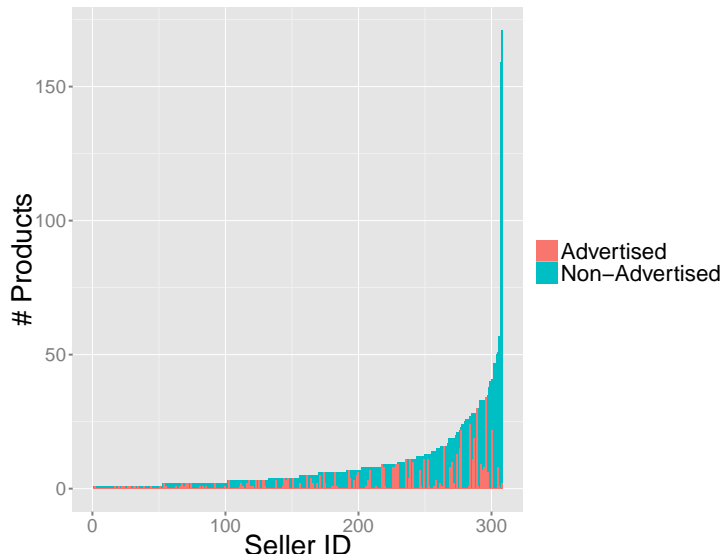
price and other observables. The first column of the table reports the estimates when price and shipping fees are separately included as covariates, whereas the second column considers the effective price (price + shipping fees). Price is not statistically significant in either specification, suggesting that pricing strategy is not primarily driven in relation to the advertising decision. Further discussion on pricing strategy is included in the next sub-section A.2.3.

Past sales is operationalized as an indicator that assumes a value of one if there have been prior sales of the item. Consistent with our previous discussion, popular products who can organically appear early in the search order advertise less (presumably because of the decreasing marginal returns to exposures). Analyzing text description in the product detail pages reveals that about 20% of the sellers include URL or sellers' website addresses to explicitly nudge consumers to redirect, and these are the sellers who seem to benefit more from advertising.

In addition, the products with non-refundable policy advertise less, and the estimates for category/material dummies suggest that bracelets, silver-made and stone-made products advertise more frequently. Lastly, the probability of advertising a given product is lower for sellers with many listings, because the information value of advertising is likely lower for larger advertisers (Blake et al. 2015). To control for the difference between casual sellers and big sellers, we further categorize sellers into three groups based on the product listing distribution (Figure 10); Brand Group 1 is the sellers with more than 150 product listings, Brand Group 2 is the sellers with product listings between 25 and 150, and the rest are Brand

2

Table 9:   Other Observables and Advertising Decisions

Variable	Specification (1)	Specification (2)	Specification (3)	Specification (4)
Constant	0.20 (0.33)	−0.58 (0.17)	−0.65 (0.32)	**−1.42** (0.22)
Price	0.001 (0.002)	–	0.001 (0.002)	–
Shipping Fees	**−0.29** (0.10)	–	**−0.28** (0.10)	–
Effective Price	–	−0.0002 (0.002)	–	0.0004 (0.002)
#Total Purchases > 0	**−0.48** (0.18)	**−0.47** (0.18)	**−0.61** (0.19)	**−0.60** (0.19)
Include URL	**0.53** (0.11)	**0.52** (0.11)	**0.52** (0.11)	**0.51** (0.11)
Refundable	**0.47** (0.11)	**0.45** (0.10)	**0.50** (0.11)	**0.48** (0.10)
Log(# products per brand)	**−0.43** (0.015)	**−0.44** (0.045)	−0.05 (0.09)	−0.06 (0.09)
Brand Group 1	–	–	**−2.93** (0.44)	**−2.92** (0.44)
Brand Group 2	–	–	**−0.47** (0.17)	**−0.46** (0.17)
Category Dummies	yes	yes	yes	yes
Material Dummies	yes	yes	yes	yes
BIC ($N = 2853$)	2747.7	2748.0	2699.8	2699.6

Group 0. While this grouping reduces differences in sellers to a trinary variable, it captures the systematic difference in advertising probabilities (Specification (3) and (4)).

A.2.3   Pricing Decisions

Seller Pricing and Seller Advertising   Although seller pricing decisions are beyond the scope of this paper, our analysis presumes that the correlation between pricing and advertising decisions are modest. Accordingly, we conduct an additional regression analysis of price on advertising status, and include brand fixed effects (see Table 10). We find no significant relationship, suggesting the plausibility of the exogenous pricing assumption we employ.

Table 10:   Pricing and Advertising Decisions

Variable	Estimates		
Constant	**19.5** (0.49)	**25.5** (2.52)	**25.5** (2.43)
Advertising (Opt in == 1) Dummy	−0.85 (1.10)	−0.76 (1.25)	−0.89 (1.20)
Brand Dummies	–	yes	yes
Material Dummies	–	–	yes
Category Dummies	–	–	yes
Adjusted R^2($N = 2853$)	0.000	0.61	0.64

Seller Pricing and Platform Fees   In our analysis we have presumed pricing strategy is exogenous to the decisions made by the marketplace platform. However, under the counterfactual scenario in which the fee structure is changed, it is possible that sellers significantly raise/lower prices in response to the changes in fee structure. To address this concern, we collect additional price information for 513 products we find to be listed in sellers' own websites or other selling channels (e.g. general e-commerce platforms, mobile apps). We note that the seller does not pay commissions if a product is sold on own website, but incur

fees in various amounts if it is sold elsewhere. Accordingly, in Table 11, we regress log price on own website dummy and product level fixed effects. The coefficient for own website dummy is not significant, (with only 1.9% change in price), supporting our modeling assumption that a single price is exogenously set across all selling channels and is not adjusted in response to the different levels of fees imposed in different platforms.

Table 11:   Pricing across Selling Channels

Parameter	Estimates
Constant	**2.71** (0.11)
Own Website Dummy	-0.019 (0.020)
Product Dummies	yes

B   Model

B.1   State Transitions and Consumer Beliefs

We assume that consumers know the distribution of product characteristics available on the site, and formulate rational beliefs based on product attribute transition. The states on product attribute transition include external attributes, $\mathbf{Z}$, and internal attributes, $\mathbf{X}$. Conditioned on the product attribute transition, consumer's belief system can be characterized by the maximum utility of the items in the consideration set, u^*, and the information available on the product listing pages, $\mathbf{Z}$.

Attribute State Transitions   Let T be the total number of products available on the site, and

$h\left(\mathbf{Z}_{j(1)}, \mathbf{X}_{j(1)}, ..., \mathbf{Z}_{j(T)}, \mathbf{X}_{j(T)}\right)$ be the joint distribution of product attributes. In the context we consider, all consumers are presented with the same order of products, thus the distribution is not subscripted by i. To factor h, we assume a first order Markov process on $\{\mathbf{Z}_j, \mathbf{X}_j\}$ such that

$$h\left(\mathbf{Z}_{j(1)}, \mathbf{X}_{j(1)}, ..., \mathbf{Z}_{j(T)}, \mathbf{X}_{j(T)}\right) = h(\mathbf{Z}_{j(1)}, \mathbf{X}_{j(1)}) \prod_{t=2}^{T} h(\mathbf{Z}_{j(t)}, \mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t-1)}, \mathbf{X}_{j(t-1)})$$

$$= h_1(\mathbf{X}_{j(1)} \mid \mathbf{Z}_{j(1)}) h_2(\mathbf{Z}_{j(1)}) \prod_{t=2}^{T} h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)}, \mathbf{Z}_{j(t-1)}, \mathbf{X}_{j(t-1)}) h_2(\mathbf{Z}_{j(t)} \mid \mathbf{Z}_{j(t-1)}, \mathbf{X}_{j(t-1)})$$

To simplify h_1, we assume that $\mathbf{Z}_{j(t)}$ is a sufficient statistic for $(\mathbf{Z}_{j(t-1)}, \mathbf{X}_{j(t-1)})$ in predicting $\mathbf{X}_{j(t)}$. That is, conditional on having the information on $\mathbf{Z}_{j(t)}$, $(\mathbf{Z}_{j(t-1)}, \mathbf{X}_{j(t-1)})$ is not informative of $\mathbf{X}_{j(t)}$. For example, this condition will be satisfied if the price information about $(t-1)$th product has no additional information in predicting the quality of t-th product

when we have t-th product price information. Also this condition will be satisfied if product attributes at position $(t-1)$ are independent of those at position t. Also for h_2, we consider ranking algorithm shown on product listing page such that h_2 only depends on $\mathbf{Z}_{j(t-1)}$ and is independent of $\mathbf{X}_{j(t-1)}$ (e.g. sort by price lowest to highest where price is shown on the product listing page as an external attribute). In sum, we simplify h and use

$$h\left(\mathbf{Z}_{j(1)}, \mathbf{X}_{j(1)}, ..., \mathbf{Z}_{j(T^r)}, \mathbf{X}_{j(T)}\right) = h_1(\mathbf{X}_{j(1)} \mid \mathbf{Z}_{j(1)}) h_2(\mathbf{Z}_{j(1)}) \prod_{t=2}^{T} h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)}) h_2(\mathbf{Z}_{j(t)} \mid \mathbf{Z}_{j(t-1)})$$

Belief State Transitions   The belief state transitions can be expressed as

$$\begin{aligned}
f_1^s\left(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}\right) &= h_2(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}) \\
f_0^c\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) &= \mathbf{1}\left(u_{it}^* = u_{it-1}^*\right) \\
f_1^c\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) &= f^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right)
\end{aligned} \tag{18}$$

The first line indicates consumer's belief on transition of $\mathbf{Z}_{j(t+1)}$ when search continues, and the actual empirical distribution h_2 is used for this rational belief. The second line represents the state transition when consumer does not consider. In this case, the maximal utility in hand stays the same. The third line is for the case when consumer does consider product $j(t)$, and the maximal utility u_{it}^* is believed to transit with distribution $f^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right)$.

Using the iid $N(0, \sigma_\epsilon^2)$ assumption made on ϵ_{ij} and the additive separability of utility specification, the last piece can further be decomposed into

$$f^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) = \begin{cases} \int_{\mathbf{X}_{j(t)}} \Phi\left(\frac{u_{it}^* - \mathbf{X}_{j(t)}\alpha - \mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)}) & \text{when } u_{it}^* = u_{it-1}^* \\ \int_{\mathbf{X}_{j(t)}} \frac{1}{\sigma_\epsilon}\phi\left(\frac{u_{it}^* - \mathbf{X}_{j(t)}\alpha - \mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)}) & \text{when } u_{it}^* > u_{it-1}^* \end{cases} \tag{19}$$

where ϕ and Φ are pdf and cdf of standard normal distribution respectively. The first line indicates the probability that the product under consideration yields lower utility than u_{it}^*, the maximal utility in the consideration set formed so far. The second line presents the probability of finding a better product. Because a consumer takes only the maximum in his consideration set, this distribution is truncated below. As u_{it-1}^* a consumer has in his hand increases, the expected benefit of consideration decreases if all others are the same.

B.2   Additional Discussion on Sequential Search Process

In this section, we discuss how our model departs from Weitzman's seminal sequential search framework (Weitzman 1979), which has been the cornerstone for modeling sequential search process in many empirical papers (Kim et al. 2010, Koulayev 2013, Chen and Yao 2014).

In Weitzman and the related sequential search literature, the consumers are assumed to rank the alternatives by reservation utilities, and the selection rule is such that the items are searched in the order of reservation utilities. With a constant search cost per

alternative, reservation utility is constant across searches, and the consumer always buys the last one searched (the no recall hypothesis in De los Santos et al. 2012). Thus consumers' revisit behaviors are rationalized by (i) increasing search cost (that is, the reservation utility decreases as in Koulayev 2013), (ii) consumer's learning (De los Santos et al. 2013), or (iii) state dependence and a search funnel (Bronnenberg et al. 2016).

In our search model, a consumer is presented with an *exogenous* search sequence, and the optimal stopping problem more closely resembles Rust's replacement model (Rust 1987, Schiraldi 2011, Seiler 2013). The uniqueness of the solution is guaranteed under the assumption that a single terminal choice (purchase) is being made.[41] As the maximum utility of the items in the consideration set, u^*, increases, the expected increase in u^* from an additional search (or consideration) decreases, which in turn decreases the probability of continuing search (or considering an item) with respect to u^*. Even with a constant search cost per alternative, the consumer is allowed to recall in our model, as the maximum utility u^* could have been attained prior to the very last step of the search process. That is, the consumer first forms a consideration set, and chooses the best alternative within the set after the search terminates, which may not be the last one searched or considered. In this regard, we provide an additional framework for rationalizing consumers' recall behavior, consistent with the findings reported in De los Santos et al. 2012, Koulayev 2013 and Bronnenberg et al. 2016.

C   Estimation

C.1   The Consumer Model

C.1.1   Derivation of Likelihood for Consideration, Search, and Purchase

In this section, we derive closed form expression for joint likelihood of consideration, search and purchase.

Consideration Decision Likelihood at Position t   The likelihood of observing consideration decision d_{it}^c, based on the (observed and unobserved) states can be defined as

$$\mathcal{L}_t^{consider}\left(d_{it}^c \mid u_{it-1}^*, \mathbf{Z}_{j(t)}; \Theta_1\right)$$
$$= \left[p_0^c\left(u_{it-1}^*, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d_{it}^c=0)} \times \left[1 - p_0^c\left(u_{it-1}^*, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d_{it}^c=1)} \quad (20)$$

where $p_0^c\left(u_{it-1}^*, \mathbf{Z}_{j(t)}; \Theta_1\right)$ is defined in equation (4).

---

[41]In our data, about 10% were multiple purchases (= 2 purchases) within the same search session. In such case, we assume that a new visit (search session) starts after purchasing the first item.

Search Decision Likelihood at Position t The likelihood of observing search decision d_{it}^s, based on the (observed and unobserved) states can similarly be defined as

$$
\begin{aligned}
&\mathcal{L}_t^{search}(d_{it}^s \mid u_{it}^*, \mathbf{Z}_{j(t)}; \Theta_1) \\
&= \left[p_0^s\left(u_{it}^*, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d_{it}^s=0)} \times \left[1 - p_0^s\left(u_{it}^*, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d_{it}^s=1)}
\end{aligned}
\tag{21}
$$

where $p_0^s\left(u_{it}^*, \mathbf{Z}_{j(t)}; \Theta_1\right)$ is given by equation (8).

Consumer Choice Decision Likelihood at Position t Let T_i^s reference the position where individual i chooses to stop searching such that $d_{iT_i^s}^s = 0$. Also denote T_i^p as the position in the search sequence where the purchased product is presented to the consumer, such that $d_{ij(T_i^p)}^p = 1$ (If the consumer chooses the outside option of not purchasing, then $d_{ij(T_i^p=0)}^p = 1$). The final consideration set $\Gamma_i = \Gamma_{iT_i^S}$ contains $K_{iT_i^S}$ number of products, and we index them as $\{1, ..., p^*, ... K_{iT_i^S}\}$ in the order encountered for consideration. Further we define $t(p)$ as the search sequence position of pth indexed product in the consideration set, such that $t(p^*) = T_i^p$.

This ordering suggests three partitionings for choice; first, those items that a consumer did not choose prior to finding the chosen alternative $\{1, ..., (p^* - 1)\}$; the chosen alternative $\{p^*\}$; and third, those items the consumer did not choose after finding the chosen alternative $\{(p^* + 1), ..., K_{iT_i^S}\}$. The cases of the considered items not chosen prior to the chosen alternative differ from those considered items encountered after the chosen alternative. More specifically, we know that all items considered after the chosen item will not have higher utility than the highest so far, i.e., the chosen item; thus it is not possible for u^* to increase with consideration. However, for items not chosen prior to the chosen alternative, u^* can increase with each item considered, even though u^* will not be higher than the chosen alternative. Thus, when determining how choice affects the likelihood, we need to explicitly condition on the order in which the considered item is encountered. In light of the foregoing discussion, we incorporate choice information into inference for the latent variable u_{it}^* transition as follows:

1. **Items considered prior to the purchased item** : when $t(p) \leq T_i^p - 1$

   In this case, the reservation utility u_{it}^* weakly increases and the transition probability of u_{it}^* can be characterized as[42]

$$
f_1^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}, \mathbf{X}_{j(t)}\right) = \begin{cases} \Phi\left(\frac{u_{it}^* - \mathbf{X}_{j(t)}\alpha - \mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) & \text{when } u_{it}^* = u_{it-1}^* \\ \frac{1}{\sigma_\epsilon}\phi\left(\frac{u_{it}^* - \mathbf{X}_{j(t)}\alpha - \mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) & \text{when } u_{it}^* > u_{it-1}^* \end{cases}
$$

2. **The chosen item** : when $t(p) = T_i^p$

   If a product is bought at position $t(p)$, this product must yield the maximal utility

---

[42]In the likelihood of unobserved state u_{it}^* transition, the product detail page information $\mathbf{X}_{j(t)}$ is included as a state space. This is different from the consumer's beliefs on u_{it}^*.

among the ones considered so far. If we consider a finely discretized space for u_{it}^* or a continuous case, u_{it}^* must be strictly greater than u_{it-1}^*.

$$f_2^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}, \mathbf{X}_{j(t)}\right) = \frac{1}{\sigma_\epsilon}\phi\left(\frac{u_{it}^*-\mathbf{X}_{j(t)}\alpha-\mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) \text{ as } u_{it}^* > u_{it-1}^*$$

3. **Items considered after the chosen item** : when $T_i^p < t(p) \le T_i^s$

   If a product is considered after T_i^p but has not been purchased, the associated utility found at position $t(p)$ should not be greater than $u_{iT_i^p}^*$.

$$f_3^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}, \mathbf{X}_{j(t)}\right) = \Phi\left(\frac{u_{it}^*-\mathbf{X}_{j(t)}\alpha-\mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) \text{ as } u_{it}^* = u_{it-1}^*$$

Combining three cases, the likelihood from choice decision incorporated into the transition of unobserved u_{it}^*, can be written as

$$\mathcal{L}_t^{purchase}\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}, \mathbf{X}_{j(t)}\right) = \left[\mathbf{1}\left(t \le T_i^p - 1\right)f_1^u\left(\cdot\right) + \mathbf{1}\left(t = T_i^p\right)f_2^u\left(\cdot\right) + \mathbf{1}\left(T_i^p < t \le T_i^s\right)f_3^u\left(\cdot\right)\right]^{\mathbf{1}\left(d_{it}^c=1\right)}$$
$$\times \left[\mathbf{1}\left(u_{it}^* = u_{it-1}^*\right)\right]^{\mathbf{1}\left(d_{it}^c=0\right)} \tag{22}$$

where the second line represents the case where t-th positioned product in the search sequence is not considered, and hence $u_{it}^* = u_{it-1}^*$.

Combining Search, Consideration, and Choice We define the total likelihood of observing the whole path of choices $\mathbf{d}_i = \{d_{i1}^c, ..., d_{iT_i^s}^c, d_{i1}^s, ..., d_{iT_i^s}^s, d_{i1}^p, ..., d_{iT_i^s}^p\}$ based on the (observed and unobserved) states as

$$\mathcal{L}(\mathbf{d}_i \mid u_{i0}^*, ..., u_{iT_i^s}^*, \mathbf{Z}, \mathbf{X}; \Theta_1)$$
$$= \prod_{t=1}^{T_i^s}\mathcal{L}_t^{consider}\mathcal{L}_t^{search}\mathcal{L}_t^{purchase}$$

where $\mathcal{L}_t^{consider}$, $\mathcal{L}_t^{search}$, and $\mathcal{L}_t^{purchase}$ are defined in equations (20), (21), and (22) respectively. This total likelihood is derived from multiplying over the likelihood of consideration and search decisions at $t = 1, ..., T_i^s$, and the transition of unobserved u^* is represented within $\mathcal{L}_t^{purchase}$.

Integrating Out Unobservable States Now we define the likelihood of observing $\mathbf{d}_i = \{d_{i1}^c, ..., d_{iT_i^s}^c, d_{i1}^s, ..., d_{iT_i^s}^s, d_{i1}^p, ..., d_{iT_i^s}^p\}$ based only on the observed states by integrating out over the unobservables $(u_{i1}^*, ..., u_{iT_i^s}^*)$.

$$L_i(\Theta_1^g) = \int_{u_{iT_i^s}^*} ... \int_{u_{i1}^*} \int_{u_{i0}^*} f^u\left(u_{i0}^*\right)\mathcal{L}(\mathbf{d}_i \mid u_{i0}^*, ..., u_{iT_i^s}^*, \mathbf{Z}, \mathbf{X}; \Theta_1^g)$$

The initial probability $f^u\left(u_{i0}^*\right)$ is the distribution of outside option value $f^u\left(\epsilon_{i0}\right) = \phi(\epsilon_{i0})$. Once we fix u_{i0}^*, the transition of $u_{it}^* \mid u_{it-1}^*$ is governed by $\mathcal{L}_t^{purchase}$ as discussed above. This likelihood ensures that the purchased product has the highest utility among all considered

products. Further, the log-likelihood of the sample data is given by

$$L(\Theta) = \sum_{i=1}^{I} ln \left(\sum_{g=1}^{G} \lambda^g L_i(\Theta_1^g) \right)$$

where we integrate out latent class consumer heterogeneity.

C.1.2 Solving the Dynamic Problem

We specify the consumer decision to be an infinite horizon problem for three reasons. First, we find that the consumers in our data search quite extensively, yet the search is never terminated at the last product available on the website. Thus, in our empirical setting, it is reasonable to assume that the consumer faces stationary value functions conditional on the states $(u_t^*, \mathbf{Z}_t)$. Second, we believe that the belief state transition can be represented as stationary conditional on the attributes Z. Third, although our estimation method can accommodate the finite horizon setting in which the future value terms are obtained via backward recursion for every search step t, the infinite horizon specification lowers the computational cost as the future value terms are computed using contraction mapping only once for a given set of parameters. Hence, we solve the dynamic search as an infinite horizon problem where stopping search is an absorbing state.

   We estimate the consumer model using MLE in the outer loop (parameter estimation) and value function iteration for the inner loop (future value terms and resulting choice probabilities conditioned on those parameters). The steps are as follows:[43]

1. Outer loop: Starting with the iteration step $iter = 0$, initialize the consumer model parameters $\Theta_1^{iter} \equiv (\alpha^{g,iter}, \beta^{g,iter}, \gamma_1^{g,iter}, \gamma_2^{g,iter}, \lambda^{g,iter})$ $g = 1, ..., G$.

2. Inner loop: Starting with the iteration step $k = 0$, initialize the value functions, $Emax^{search, k}$.

   (a) Given $Emax^{search, k}$, compute the conditional value function for the consideration decision based on equation (2). Then these conditional value functions are used to

---

[43]The value function states are discretized as follows. Price is discretized into 15 grid spaces based on their quantiles. The grid points for #likes include 0 and 1 as these are commonly observed states. In addition, the higher values for likes are discretized into 4 grid spaces based on their quantiles (hence, there is a total 6 grid spaces for the number of likes). We consider values of u^* that lie between $u^* \in [-3, 5]$ and discretize this interval into equidistant spaces of 30. The lower bound of the u^* range is based on the idea that the initial value is drawn from $u_{i0} = \epsilon_{i0} \sim N(0, 1)$ and u^* can only increase as the search process progresses. The upper bound of the u^* is based on the maximum value of u^* over the potential range of the parameter spaces, i.e. $max(u_{ij} = \mathbf{X}_j\alpha + \mathbf{Z}_j\beta + \epsilon_{ij})$. At the parameter values estimated, $max(\mathbf{X}_j\alpha + \mathbf{Z}_j\beta) \approx 0.245$; with $\epsilon_{ij} \sim N(0, 1)$, the upper limit of 5 for u^* does not generally bind. The discretization employed assumes that the states lie at the middle value of the respective grid space. We checked the robustness of the discretization by expanding the price, the likes, and u^* dimensions by 50, 15, 50 grid spaces respectively. The end points of u^* range were also extended to $[-5, 10]$. In all cases, the estimates were stable.

compute the conditional choice probability of no consideration, p_t^c, as defined in equation (4) and also the expected future value of consideration, $Emax^{consider,k}$, as defined in equation (7).

(b) Similarly given $Emax^{consider,k}$ obtained in Step 2(a), compute the conditional value function for the search decision based on equation (6). Then these conditional value functions are used to compute the conditional choice probability of ending search, p_t^s, as defined in equation (8). Finally, the expected future value of search, $Emax^{search,k+1}$, is updated for the next iteration step $(k+1)$ using the equation (3).

3. Repeat Step 2(a) - Step 2(b) until convergence. This convergence will ensure that both the value functions and the conditional choice probabilities converge.

4. Compute the log-likelihood in equation (14), based on the converged conditional choice probabilities. Optimize the log-likelihood to compute the new set of parameters Θ_1^{iter+1}

5. Repeat Step 2 - Step 4 until we find the global maximum.

C.1.3 Identification and Purchase Data

In this exercise, we consider homogeneous consumers, and assume that there are 50 products on the platform, with a single dimension attribute for each Z and X. Z can be thought of as price displayed in the product listing page, and X can be thought of as the number of pictures available in the product detail page. One set of 50 products are randomly drawn from

$$(Z, X) \sim N \left(\begin{bmatrix} 5 \\ 2.5 \end{bmatrix}, \begin{bmatrix} 9 & 1 \\ 1 & 9 \end{bmatrix} \right)$$

A synthetic data set is generated with 100 simulations. The deep parameters used as a baseline and the estimated results are present in Table 12. σ_ϵ is normalized to be one for identification purposes, and constant functional forms were used for consideration and search costs. The recovered parameters are all close to the true values with small standard errors.

Table 12: Estimation Results from Simulated Data

	Parameter	True	Estimates (SE)	Estimates (SE) Without Purchase
α	valuation on **X**	0.5	**0.4869** (0.0788)	**0.5696** (0.1825)
β	valuation on **Z**	−1.2	**−1.2151** (0.1690)	**−1.3575** (0.7144)
γ_1	consideration cost	0.4	**0.3983** (0.0312)	**0.4029** (0.0342)
γ_2	search cost	0.3	**0.3082** (0.0093)	**0.3108** (0.0149)

The last column shows the results when purchase data are ignored, and only search and consideration observations are used in estimation. Although consideration and search cost estimates are still close to the true values, the preference parameter estimates are much worse with at least twice the previous standard errors. This suggests that the identification of preference parameters are significantly enhanced when purchase data are consolidated. This is because purchase data provide additional information on how the unobserved maximal utility u_t^* transits as search progresses. For example, if a consumer considers items in position $(1, 3, 5)$, we can infer that the maximal utility found so far increases weakly with $u_1^* \leq u_3^* \leq u_5^*$. However if we also have purchase information that this consumer buys the item positioned at 3, we can further infer that the third product has the highest utility among the ones considered, that is $u_1^* < u_3^* = u_5^*$. This narrower bound on the transition of unobserved maximal utility significantly narrows down the bounds for preference parameters.

C.1.4 In-Sample Model Fit

Table 13 presents the in-sample model fit of the consumer model, where one random set of 908 visits is simulated and the key statistics are compared to those of the data. The overall fit to the aggregate moments is good, and the heterogeneity on the cost parameters significantly improves the fit of the distribution.

C.2 The Advertiser Model

C.2.1 Beliefs on Product Placement

The platform's ranking algorithm displays products in the order of rank scores:

$$
\begin{aligned}
Rank_{j,t,d_j^a,\mathbf{d}_{-j}^a} &= Rank\left(\text{Own Score}_{jt}, \text{Others' Scores}_{-jt}\right) \\
&= Rank\left(\text{Popularity}_{jt}, \text{Slot Adjust}_{jt}, \text{Days Listed}_{jt}, \text{Advertising}_{jt}, \text{Others' Scores}_t\right)
\end{aligned}
\tag{23}
$$

where the second line reflects how the own rank score (Own Score) is a function of the popularity score, slot adjustment score, days listed, and the advertising score ($=$ days listed$\times$advertising status). Because advertisers do not observe all components, or how they are combined, we need to generate a model of advertiser beliefs, denoted $\widehat{Rank}$. Of all the components that enter the rank function, advertisers know only their own advertising status (d_j^a) and days listed. They do not know their popularity score or slot adjustment score. Roughly speaking, the slot adjustment score depends on rank and days listed, whereas the popularity score is a function of rank, days listed, as well as other unobserved characteristics that drive more clicks and likes conditional on the product position. Substituting these into

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Table 13: The Consumer Model In-Sample Fit

# Per Visit		Min	Median	Mean	Max	SD
Search	Data	7	20	79	4867	283.5
	1 Segment	1	55	77.8	488	75.0
	3 Segments	1	27	63.7	2993	198.5
Consideration	Data	0	0	0.8	44	3.1
	1 Segment	0	0	0.84	8	1.2
	3 Segments	0	0	0.69	22	1.2
Demand (choice)	Data	0	0	0.04	1	0.2
	1 Segment	0	0	0.06	1	0.23
	3 Segments	0	0	0.04	1	0.2
#considerations	Data	0	0	1.2	25	2.9
/#searches (%)	1 Segment	0	0	1.05	50	2.37
	3 Segments	0	0	0.89	50	2.58
#demand	Data	0	0	7.1	100	21.7
/#considerations (%)	1 Segment	0	0	6.87	100	21.3
	3 Segments	0	0	7.5	100	21.2

the rank function yields

$$Rank_{j,t,d_j^a,\mathbf{d}_{-j}^a} = Rank\left(\text{Popularity}(\text{Rank}_{jt}, \text{Days Listed}_{jt}, \text{Unobserved}_j),\right.$$

$$\text{Slot Adjust}(Rank_{jt}, DaysListed_{jt}),$$

$$\left.\text{Days Listed}_{jt}, \text{Advertising}_{jt}, Others'Scores_t\right)$$

$$Rank_{j,t,d_j^a,\mathbf{d}_{-j}^a} = Rank\left(\text{Unobserved}_j, \text{Days Listed}, \text{Advertising}_{jt}, \text{Others' Scores}_t\right)$$

As the unobserved part is a component of popularity score that is not explained by the rank and days listed, a proxy measure called "organic strength" is constructed for each product j by regressing the popularity score at product-day level on days listed and observed product position using generalized additive model, then taking the mean of the residuals. Although the seller may not know the underlying popularity score for each day, we presume that the seller knows its own product's inherent general popularity level (unobserved characteristics) with respect to others, which is captured by including the organic strength term into the seller's information set. Lastly, advertisers do not know other advertisers' scores, so we presume advertisers instead condition on the aggregate states of competing advertisers' decisions when forming own rank beliefs. The rationale is that a greater number of competing advertisers

leads to a lower rank. In sum, the advertiser's belief on the product placement for a given day t is assumed to be based on a generalized additive model

$$\widehat{Rank_{j,t,d_j^a,\mathbf{d}_{-j}^a}} = g\left(\text{Organic Strength}_j, \text{Days Listed}_{jt}, d_j^a, E_t(\mathbf{d}_{-j,}^a), J_t\right)$$

where d_j^a is own advertising strategy, $E_t(\mathbf{d}_{-j}^a)$ is the *aggregate states* of others' advertising strategies, and J_t is the total number of products available.

Figure 11:   Beliefs on Product Placement
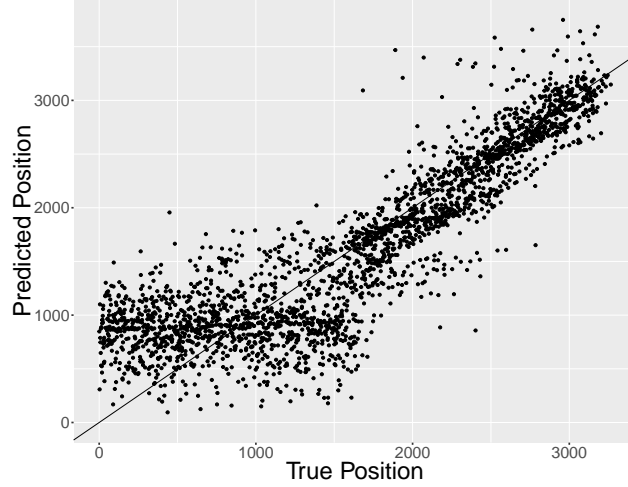
In Figure 11, we plot product position based on the platform's algorithm on the x-axis and the sellers' beliefs on the y-axis on a given day. Although the latter bases only on the aggregate states and own individual states, sellers' beliefs are approximated to be close to rational expectations.

C.2.2   Solving the Advertiser Problem

We estimate the advertiser model in three stages, and these stages are described next.

Stage 1 - Estimate Seller's Beliefs About Platform Ranking Algorithm   First, estimate the function governing sellers' beliefs on product placement as described in sub-section 4.2.1, that is we estimate g function in equation (15).

Stage 2 - Estimate Effect of Advertising on Product Placement and Consumer Responses

1. Compute product placement for each advertising decision
   On a given day t, given seller's information set $\left(d_j^a, E_t(\mathbf{d}_{-j}^a), J_t, \text{Days Listed}_{jt}, \text{Organic Strength}_j\right)$, compute the belief about product $j's$ placement when advertising $\left(\widehat{Rank_{j,t,d_j^a=1,\mathbf{d}_{-j}^a}}\right)$ and not advertising $\left(\widehat{Rank_{j,t,d_j^a=0,\mathbf{d}_{-j}^a}}\right)$ using the function g estimated in Stage1. For

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estimation, we compute $\left(E_t(\mathbf{d}^a_{-j}),\ J_t\right)$ under the observed advertising strategies, and use these two statistics as the aggregate beliefs.

2. Compute consumer responses based on product placement beliefs $\left(\widehat{Rank}_{j,t,d^a_j=0,\mathbf{d}^a_{-j}},\ \widehat{Rank}_{j,t,d^a_j=1,\mathbf{d}^a_{-j}}\right)$
   Using the consumer demand model, simulate consumer demand, consideration, and choice $\left(\widehat{D_{j,t,,d^a_j,\mathbf{d}^a_{-j}}},\ \widehat{C_{j,t,d^a_j,\mathbf{d}^a_{-j}}},\ \widehat{I_{j,t,d^a_j,\mathbf{d}^a_{-j}}}\right)$ by displaying product j at position $\left(\widehat{Rank_{j,t,d^a_j,\mathbf{d}^a_{-j}}}\right)$.
   This is done at the daily level, and these simulated responses are aggregated across time periods to form product j's lifetime demand, consideration, and choice which are entered into equations (11) and (12).[44]

Stage 3 - Estimate Seller Model Parameters

1. Starting with the iteration step $iter = 0$, initialize the advertiser model parameters $\Theta^{iter}_2 \equiv \left(\theta^{iter},\ \theta^{D,iter},\ \theta^{C,iter},\ \theta^{I,iter},\ \delta\right)$.

2. Using equation (13), compute the advertising probability for product j based on the aggregated consumer responses obtained in Stage 2, when advertising $\left(\widehat{D_{j,d^a_j=1,\mathbf{d}^a_{-j}}},\ \widehat{C_{j,d^a_j=1,\mathbf{d}^a_{-j}}},\ \widehat{I_{j,d^a_j=1,\mathbf{d}^a}}\right.$
   and not advertising $\left(\widehat{D_{j,d^a_j=0,\mathbf{d}^a_{-j}}},\ \widehat{C_{j,d^a_j=0,\mathbf{d}^a_{-j}}},\ \widehat{I_{j,d^a_j=0,\mathbf{d}^a_{-j}}}\right)$ and the given set of parameters Θ^{iter}_2.

3. Compute the log-likelihood in equation (16), based on the advertising probabilities computed. Optimize the log-likelihood to compute the new set of parameters Θ^{iter+1}_2

4. Repeat Step 2 - Step 3 until we find the global maximum.

C.2.3   Computing Equilibrium Advertising Strategies for the Policy Simulations

As described in Stage 2 above, in estimation we use the actual advertising strategies to compute $\left(E(\mathbf{d}^a_{-j}),\ J\right)$. However, these strategies will change as the site changes its policies. Hence, in policy simulations, we need to iterate over the sellers' beliefs and the advertising decisions until convergence. This convergence will ensure that the aggregate beliefs are consistent with the underlying advertisers' decisions in equilibrium.[45] The steps follow:

1. Estimate sellers' beliefs about platform ranking algorithm
   For the policy simulation where we do not change the ranking algorithm (i.e. where we only change the fee structure), we use the same g function (equation (15)) used in

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[44]We aggregate consumer responses up to the point the (belief on) product position reaches 2000. As consumers median search length is 20 (mean 79), this constraint does not impact aggregation.

[45]Although we do not provide proof for existence, we did not encounter convergence issue in our implementation. Related, in a dynamic auction setting Iyer et al. 2014 proves existence of mean field equilibrium under mild assumptions.

the estimation. For the policy simulation where we do vary the ranking algorithm, g function is updated. That is, the product position on the left hand side of equation (15) is simulated based on the score inputs and the platform's new ranking algorithm under the counterfactual scenario, then new sellers' beliefs are constructed by estimating this g function again.

2. Starting with the iteration step $k = 0$, initialize the advertising strategies $\mathbf{d}^{a,k}$. We start from the observed advertising strategies in the data.

3. For each product j, obtain the aggregate beliefs $\left(E(\mathbf{d}^{a,k}_{-j}), J \right)$ given $\mathbf{d}^{a,k}$. We also update consumers' belief transition in equations (18) and (19) based on $\mathbf{d}^{a,k}$ and platform's actual ranking algorithm.

4. Next step is to estimate the effect of advertising on product placement and consumer responses (search, consideration and choice). To compute this, we run Steps 1 - 2 in Stage 2 of sub-section C.2.2.

5. Compute the new advertising strategy for product j, $d^{a,k+1}_j$. This can be achieved by running Step 2 in Stage 3 of sub-section C.2.2, based on the estimated parameters $\Theta_2 = \left(\theta, \theta^C, \theta^C, \theta^I, \delta \right)$ from the advertiser model.

6. Stack the updated advertising probabilities $d^{a,k+1}_j$ into $\mathbf{d}^{a,k+1}$

7. Iterate Step 3 - Step 6 above until convergence. This ensures the individual decisions are consistent with the aggregate expectations.