Monetizing Online Marketplaces

Hana Choi Carl F. Mela*

June 26, 2018

Abstract

This paper considers the monetization of online marketplaces. These platforms trade-off fees from advertising with commissions from product sales. While featuring advertised products can make search less efficient (lowering transaction commissions), it incentivizes sellers to compete for better placements via advertising (increasing advertising fees). We consider this trade-off by modeling both sides of the platform. On the demand side, we develop a joint model of browsing (impressions), clicking, and purchase. On the supply side, we consider sellers' valuation and advertising competition under various fee structures (CPM, CPC, CPA) and ranking algorithms.

Using buyer, seller, and platform data from an online marketplace where advertising dollars affect the order of seller items listed, we find that ranking items by consumer utility lowers platform's profits as it leads to more lower-price item purchases. Combining a ranking algorithm that sorts items by expected sales revenue with a CPC auction limited to the top 5 positions improves profits the most, because this practice monetizes the highest valuations for advertising on top, while enhancing the transaction revenues in the lower positions.

Keywords: Online marketplace, E-commerce, Online advertising, Sequential search model, Dynamic discrete choice model

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

*Hana Choi is a Ph.D. student at the Fuqua School of Business, Duke University (email: hana.choi@duke.edu, phone: 734-834-0699). Carl F. Mela is the T. Austin Finch Foundation Professor of Business Administration at the Fuqua School of Business, Duke University (email: mela@duke.edu, phone: 919-660-7767). The authors thank Peter Arcidiacono, Bryan Bollinger, Garrett Johnson, Chris Nosko, Emily Wang, Sha Yang, and seminar participants at the 2016 International Choice Symposium, the 2016 Economics of Advertising Conference, the 2017 Summer Institute in Competitive Strategy, the 2017 National Bureau of Economics Research, Boston University, the University of Chicago, Columbia University, Duke University, Duke-UNC Brown Bag, Emory University, Erasmus University, Harvard University, the University College London, the University of Alberta, the University of Minnesota, the University of Pittsburgh, The University of Rochester, the University of Southern California, and Yale University for comments and suggestions.

1 Introduction

1.1 Overview

With buyers on one side and third party merchants on the other, online marketplaces are a two-sided platform of substantial economic importance. The market capitalization of Alibaba, the world's largest online marketplace, was around \$458 billion in the first quarter of 2018, and the market capitalization of Amazon, the largest online retailer in the U.S., was over \$690 billion.[1] In 2017, 51% of units in Amazon were sold by third-party sellers,generating \$31.88 billion, up from \$22.99 billion in previous years.[2] An estimated \$1.47 trillion was transacted on the top 75 online marketplaces around the world in 2017.[3] With the rise in mobile shopping, online marketplaces are expected to continue the rapid growth in coming years.[4]

Online marketplaces' revenue models are built upon several different fee types, including (i) merchant impressions delivered to the consumers by the platform (or cost-per-mille, CPM), (ii) fees charged to merchants for clicks made by the consumers (or cost-per-click, CPC), or (iii) the cost paid per completed merchant transaction (or cost-per-action, CPA). For example, commissions on sales are a common form of CPA wherein merchants are usually charged fees per item sold as a percentage of the total sale amount, and these fees vary between 6% $\sim$ 25% depending on the platform and categories.[5] Advertising fees are commonly charged based on CPC pricing.[6] Marketplace platforms commonly consider their product display ranking algorithm in conjunction with the fee types, because listing order affects the various sources of revenue. For example, ranking items from low to high price can lower CPA fees if consumers substitute lower price goods, but can raise CPC fees if more clicks are generated.

In spite of the growth in online marketplace platforms, research is limited regarding their fee structure and ranking strategies. Accordingly, this paper considers the monetization of advertising and sales in the context of online marketplaces by considering i) how product ranking decisions affect consumers' browsing (i.e., the impressions that can be monetized

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

[2] http://www.statista.com/statistics/259782/third-party-seller-share-of-amazon-platform/

[3] https://www.digitalcommerce360.com/2018/01/11/infographic-largest-online-marketplaces-world/

[4] https://www.outerboxdesign.com/web-design-articles/mobile-ecommerce-statistics

[5] 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).

[6] 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.

via CPM), consideration (i.e., the clicks that can be monetized by CPC), and choice (which affects monetization via CPA); and ii) how ranking algorithms as well as fee structure (i.e., CPM, CPC, and CPA) affect sellers' advertising decisions and platform profits.

Toward answering these two questions, we develop a joint model of i) consumer impressions, clicks, and purchases and ii) sellers' advertising competition, where advertising behaviors take consumers' search (browsing to become aware of items and clicking to consider them) and choice (purchase) into account. Because of the interdependency across both sides of the platform (advertising can make search inefficient, thereby lowering consumer sales), a complete accounting of platform monetization requires the joint consideration of both consumer and advertiser behavior. Thus, to address our research objectives we develop a joint model of consumer and advertiser behavior on online marketplaces. Next, we discuss relevant research pertaining to both sides of the platform and how our model builds on those foundations.

1.2 Relevant Research

1.2.1 Consumer Behavior

Our consumer model builds upon Mojir and Sudhir 2016 and Chan and Park 2015, who consider the demand side problem of consumer search and product choice. Our emphasis on monetization of advertising in the online marketplace context (as opposed to spatio-temporal price search in Mojir and Sudhir 2016 and sponsored search in Chan and Park 2015) motivates several differences in modeling choices. Extending Mojir and Sudhir 2016, we decouple the timing of store search (browsing in our context) and category consideration (clicking in our context), as these are coincident decisions in Mojir and Sudhir 2016. However, in our context, we often find the absence of clicking after browsing and/or extensive browsing after the terminal click, suggesting that browsing and clicking decisions are not coincident in the online marketplace context. Moreover, as our goal is to consider the monetization of each step, it is useful to decouple them. Our model more closely hews to Chan and Park 2015, who consider sponsored search. Unlike our context, purchase is rarely observed in search advertising so the terminal click is often proxied for purchase. In the online marketplace context, wherein purchase is observed, we find that purchase rarely occurs at the last click. Hence, our consumer model decouples click and purchase decisions and accommodates the possibility that consumers purchase even the non-terminal clicked items. Our consumer model is also related to Honka et al. 2017 who formulate a simultaneous search model to ascertain how advertising influences the consumer purchase funnel, while our emphasis focuses upon sequential search in the context of an online marketplace.

1.2.2 Advertiser Behavior

The marketplace context we consider also has implications for the supply side. First, it is common that online marketplaces' revenues come from both advertising and transactions. As such, we build on Chan and Park 2015's specification for advertiser valuation by including the observed dollar value of purchases. Second, there are typically a vastly greater number of advertiser decisions observed in online marketplaces (sometimes thousands of advertisers competing for a limited number of slots). Hence, (i) it can be difficult to scale the inequality constraint approach in Chan and Park 2015, and (ii) the common knowledge assumption on valuations of other advertisers is more difficult to ensure when the number of them becomes large. To address a similar challenge in display advertising markets, Balseiro et al. 2015 and Lu and Yang 2016 use a Mean Field Equilibrium (MFE). In the MFE, advertisers condition on the aggregate stationary distribution of states rather than each competitor's, an approach that obviates the need to invoke a common knowledge assumption. By characterizing advertiser competition, we provide insights on the platform's profits and equilibrium outcomes under different fee structure and ranking algorithm. Third, because we observe both paid and non-paid listings, we consider the trade-off advertisers face in advertising and not advertising (i.e. organic ranking) (Blake et al. 2015, Simonov et al. 2015).

1.3 Key Findings

The consumer search and choice model results indicate that price and the number of pictures affect consumer preferences the most. The consumers' average marginal cost of browsing and clicking are \$0.89 and \$3.90 respectively, though there exists considerable heterogeneity in search costs across consumers. The model of advertiser behavior indicates that the typical seller's valuation from demand is negative (-4% of the transaction amount) when the seller opts-in for advertising under the current fee structure. In other words, sellers are worse off on each advertised sale. In contrast, the median valuation from a click is estimated to be \$0.13. Together, these results could suggest that clicks have a branding value because they can generate future demand for the advertiser's goods. Of note, impressions generate little value beyond clicks in our data.

Owing to consumers' high level of price sensitivity, we further find that a policy wherein the platform orders products by consumer utility or by ascending price lowers the platform's profits. Though more items are sold by reordering the product list, those that are sold are lower price items. Sorting items by past sales also reduces platform's profits, because the increase in transaction commissions does not offset the decrease in advertising commissions. On the other hand, listing items by expected transaction revenue enhances platform profits, though it reduces consumer's consumption utility. Because of the advertisers' high value for clicks and low value for sales (due to negative estimated margins for advertised goods caused by high levels of commissions imposed by the platform), policies that lower the cost-per-action/fees (CPA) such as commissions and increasing the cost-per-click (CPC) more than doubles platform profits. Moreover, this policy improves advertiser welfare because their payments are better aligned with their valuations.

Finally, platform profits can be nearly tripled by changing both the pricing mechanism and the product ranking algorithm. Specifically, by i) using a second-price CPC auction on the top 5 positions (i.e., thereby limiting the advertising slots), and ii) ordering the remaining positions (6 and lower) by expected transaction revenue generates the highest platform's profits. The intuition behind this result is that rationing the top positions monetizes the highest sellers' valuations for advertising, while the transaction revenues are enhanced by ranking slots 6 and lower by the expected revenue.[7] This outcome is illustrative of the value that accrues from considering the motivation of agents on both sides of the platform.

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 (browse, click, purchase behaviors) and sellers (advertising decisions), along with their operational details including product display ranking algorithm. Moreover, owing to the unique nature of the handcrafted items in the data, browses and clicks are extensive and advertising is frequent, 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.

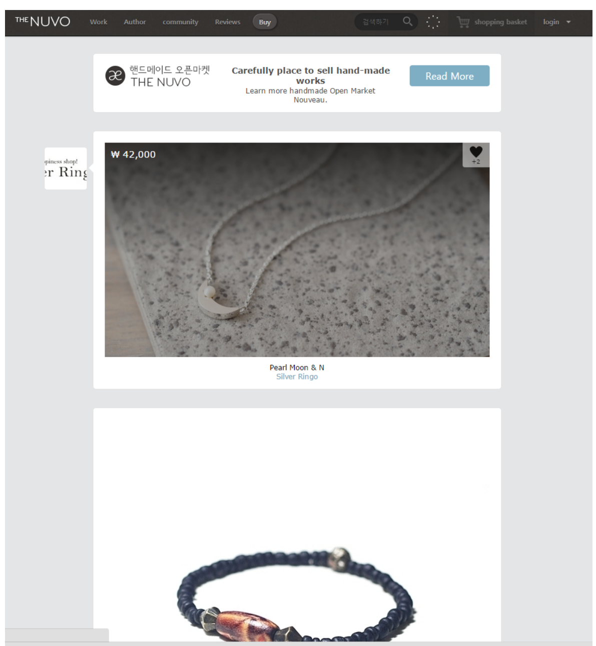
[7] In some regards this practice is similar to keyword advertising, which limits the number of sponsored search positions and orders the search ads by expected revenue.

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.[8] Figure 1 provides a screenshot of the top part of the main page. Consumers can scroll down to view more items or can interrupt browsing by clicking upon a specific product to access its product detail page and to gather additional information. Upon continuation of browsing, 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 browsing. Because 10 products are loaded per request, we do not observe where the consumer browsing exactly ends within the loaded products. Thus in the empirical analysis, consumers are assumed to have browsed all items that are loaded from the requests.[9]

Figure 1: Website Design



Information included in the "*product listing page*" (defined as the product's information

[8]The format is similar to Facebook's news feed or the design of the online marketplace Fancy (fancy.com).
[9]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 browses all 10 items loaded, we can define the last browse as the last overlay within that set. Our estimates are robust to this alternative approach for inferring the end of browsing.

presented on the main landing page) includes the item's name, seller's (brand) name, price, number of likes, and 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 (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, which are captured as the outside good in our model. [10]

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. While this algorithm is known to the researchers, it is not known to the sellers. The site presents the same list to all consumers and does not present sponsorship tags (so the consumers cannot distinguish between advertised and non-advertised listings).[11] 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 of older items acquiring higher popularity scores, the site applies a negative weight to the total number of days listed. Last, the advertising score mitigates the negative weighting on days listed, so older products can substantially increase their rank

[10] While it is feasible to consider shopping across all categories, the problem becomes substantially more complex. 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. Further discussion is included in online Appendix A.1.

[11] If ads are clearly delineated, a sponsored ad indicator can easily be added to the utility function using an indicator variable to assess whether marks have an effect over and above rank (e.g., Sahni and Nair 2016).

order in the listed items via advertising. The advertising advantage is attenuated as more sellers advertise because the gains in position are offsetting.[12]

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 numbers indicate newer products. On the x-axis, smaller numbers indicate higher display positions. 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 upper positions 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.

[12]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 browse, the product detail pages they click, 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 Feb. 2016. During the estimation sample period, $74,224$ users make $238,646$ visits to the platform.[13] We focus our attention on the main landing page visits. Excluding other category visits and main page visits with a landing followed by immediate visit to another area on the site leaves us $72,030$ users with $85,632$ visits. We further restrict our attention to the users with at least one purchase (within the estimation period, across all categories), giving us 263 users with 956 visits. 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). 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 $74,969$ total items browsed, we exclude 569 with zero prices.

2.2.2 Buyer Side Statistics

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

Visit (Search Session) We observe 263 individuals meeting our criteria, with a total of 956 visits. An individual makes 3.6 visits on average (median 2) during the sample period. These consumers browse $74,400$ products in total, among which 795 are considered, and 40 are purchased within the main page product feed.[14]

Product Search Summary statistics of consumer browsing and clicking behavior are presented in Table 1. The table indicates a mean level of 78 products browsed, and 0.8 product detail pages clicked, but there is a large standard deviation associated with each.

[13] 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 category, or continues to search after purchasing an item.

[14] The average conversion rate for an e-commerce website in Q1 2017 in the U.S. is around 2.46%, and internationally 2.48% (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%.

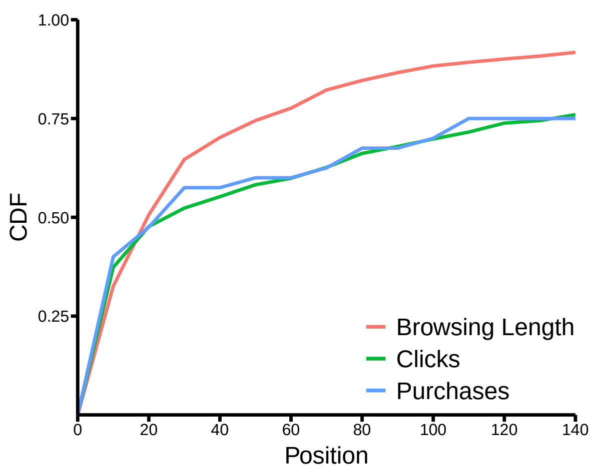
The cumulative distribution of each behavior is present in Figure 3. Consumers in our sample generally search extensively, and there exists significant heterogeneity in search across individuals. These consumers differ in length and depth of their search processes. Some browse longer and make few clicks, whereas others browse shorter and click relatively many. All point to heterogeneity present in valuations and/or costs, and that consumers might possess click costs that are different from browsing costs.

Table 1: Summary Statistics of Consumers Behavior

# Per Visit	Mean	Median	Std Dev	Min	Max
Items Browsed per Visit	78	20	277	7	4867
Clicks per Visit	0.8	0	3.0	0	44
Purchases per Visit	0.04	0	0.2	0	1
#Clicks/#Browses (%)	1.1	0	2.9	0	25
#Purchases/#Clicks (%)	7.4	0	22.2	0	100

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

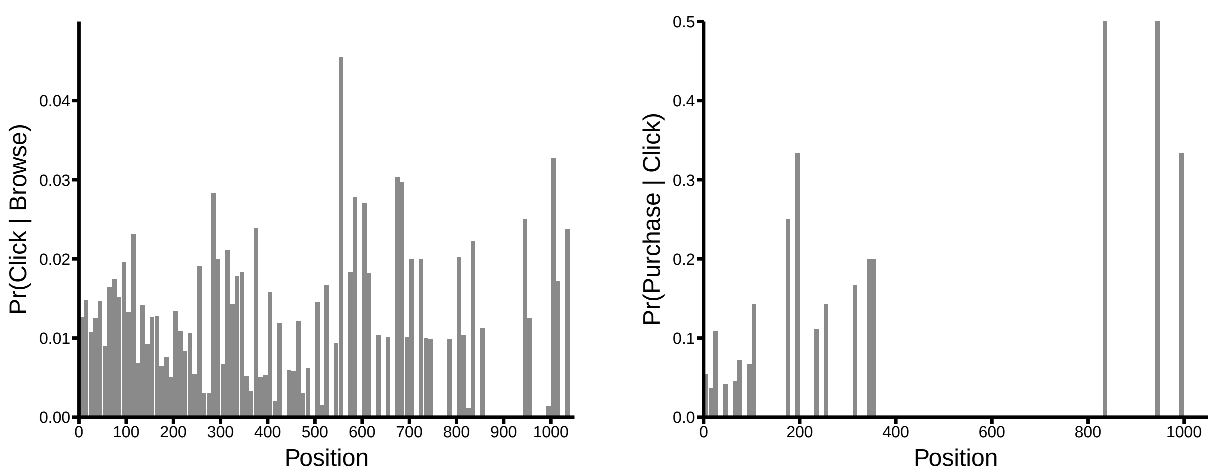
Figure 3: Browsing Length, Click, and Purchase by Position



The product ranking and placement of advertised goods can have a considerable impact on items browsed and clicked. Such effects can be amplified for consumers with larger browsing and click costs. To explore this potential, Figure 3 displays how products placed in different positions are browsed, clicked, and purchased. The product position in the display list is plotted on the x-axis (larger number means lower position in the display feed). The cumulative probability of browsing, clicking, purchase attained by the position is plotted on the y-axis. The position effect is strongest for the browsing length, and the number of browses obtained decrease exponentially with position, similar to the findings in Ansari and Mela 2003.

Conditional on browsing, however, the click likelihood does not exhibit an exponential decrease with the listing position, indicating that the magnitude of browsing costs and click 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 click conditional on browsing 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 click. Here the decrease in purchase with position is even smaller conditional on click, suggesting that preference plays a bigger role at this decision stage relative to the sunk browsing and click costs.[15] These plots are consistent with our modeling approach in that consumers first form a consideration set taking into account the preference and the costs of browsing and click, but then make a purchase decision at the end based on preference alone. In sum, all above findings suggest the desirability of explicitly modeling the purchase (demand), as well as browsing and click behaviors separately.

Figure 4: Position Effect on Click and Purchase



Top-Down Search Assumption An important assumption in our search model is that consumers browse and click products sequentially from top-to-bottom (scroll down the product feed).[16] We begin by noting that browsing must be top down when products are encountered

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

[16]A considerable literature supports top to bottom search behavior (Granka et al. 2004, Ansari and Mela 2003), and top-down can be rationalized when consumers infer advertiser's quality from the position and search optimally (Chen and He 2011, Athey and Ellison 2011). As such, top-down search behavior assumption is often invoked in the sponsored search context (Aggarwal et al. 2008, Kempe and Mahdian 2008, Chan and

Table 2: Deviations from Top-Down Search Process

Deviations in Clicks		% of Visits
# Clicks < 2		91.6%
#Clicks≧ 2	No Deviation	6.6%
	1	1.57%
	2 or more	0.21%

for the first time, because there is no way to be exposed to a later item before being exposed to an earlier one. However, this is not necessarily true for clicks. To explore this assumption further, we count the total number of occurrences in which the consumers click in the reverse rank order within each visit. Table 2 suggests that our assumption of top-down clicking is not violated for 98.2% $(91.6 + 6.6)$ of all visits.[17] In those instances in which consumers deviate from the top-down search pattern, we presume the observed browse/click 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-February 2016, but the key inputs to the ranking algorithm (popularity score, slot adjustment score) are only available after mid-November 2015. As such, we use the shorter span when estimating the advertiser model. 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 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 March 2014 when the website went

Park 2015). We similarly adopt this assumption in our online marketplace context.

[17] The percentage of visits with deviations from top-down click behavior *conditional on multiple clicks*, 21% $(= 1.78/8.4)$, is lower than reported in Jeziorski and Moorthy 2017 (28%) and much lower than Jeziorski and Segal 2015 (57%). In Jeziorski and Moorthy 2017, brand prominence largely influences consumers searching for cameras. We conjecture that handmade goods predominantly includes sellers (=brands) with few listings and little brand recognition, which may in part explain why our data exhibits stronger evidence for top to bottom browsing/clicking behavior.

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 9 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.[18]

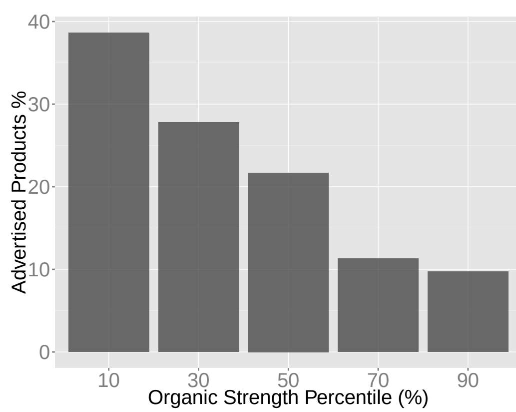
[18]We offer two potential reasons as to why advertising decisions rarely change in our context. First, it is possible for an advertiser to consider future outcomes, but just do so upon the initial listing decision based on a net present value. Second, we note that there are potentially substantial costs to monitoring the states of the market each day to change advertising over the duration of a listing.

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 a higher organic position in the product list. 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 product list advertise less, suggesting strategic behavior on the part of the advertiser.

Figure 5: Mean Organic Position and Advertising Percentage



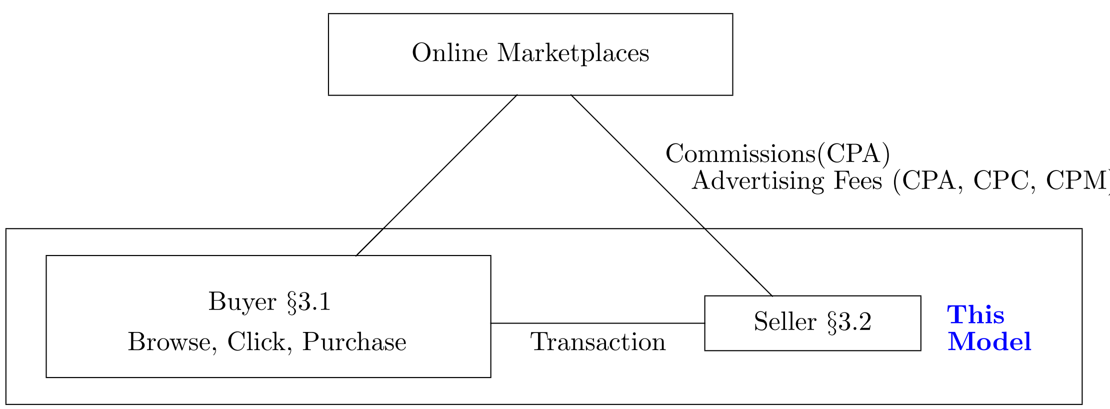
The observed pattern that organically highly ranked products advertise less than those organically ranked lowly suggests diminishing marginal returns to impressions. To the extent that diminishing marginal returns exist, one might expect strategic sellers at the bottom of the queue to be more disposed to advertise in order to be bumped up into the range of searched goods and gain the first impressions. 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]

[19]In online Appendix A.2.2, we document some of the important observables that suggest different

3 Model

In this section, we present a structural model encompassing the online marketplace. This model contains two components; i) a model of consumer browsing (impressions), clicking (selection of product detail pages), and purchases (choice); and ii) a model of sellers' advertising decisions wherein sellers compete for positions in order to maximize their valuations from consumer impressions, clicks, and purchases. 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. Thus, we solve the problem 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.

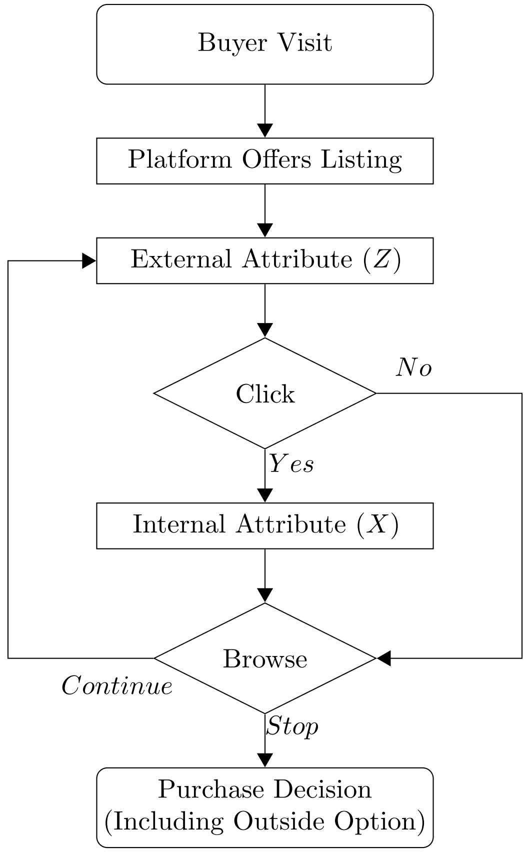
1. **Visit**: A consumer first decides whether or not to visit the e-commerce website (start search session). We take the consumer's visit decision as exogenously given. That is, the consumer's visit decision is independent of other consumers' behavior, sellers' advertising behavior, and the platform's ranking algorithm.[20] [21]

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.

[20]Like many scanner data papers, we focus on what happens conditional on store visit and take the shopping trip decision as given. With this simplifying assumption, we take the market size (consumer visits) to be fixed for the counterfactual exercises.

[21]The platform does not provide refinement options like sorting and filtering on the main landing page. As

Figure 7: Consumer Model



2. **Product Search**: Product search consists of two stages; browsing (which generates impressions) and clicking (on a product detail page yielding additional information about the items). Upon first 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 the first item incurring a click cost, or browse the next product on the list while incurring a browsing cost; that is we presume a sequential search process. This leads to the following sequence of steps:

   - **Clicking 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

such, our consumer model abstracts away from sorting and filtering decisions and instead considers the effect of sorting by price and past sales as counterfactual exercises.

into the consideration set by accessing (clicking) its product detail page. Once clicked, 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 click decision is made, the consumer decides whether to browse the $(t+1)$th position product. We present the click model in Section 3.1.2.

- **Browsing or Exit Decision**
  Conditioned on the information obtained in searching so far (the set $\{\mathbf{Z}_1, \mathbf{Z}_2, ..., \mathbf{Z}_t, d_1^c \cdot (\mathbf{X}_1, \epsilon_1), d_2^c \cdot (\mathbf{X}_2, \epsilon_2), ..., d_t^c \cdot (\mathbf{X}_t, \epsilon_t)\}$, where $d_t^c = 1$ if an item is clicked in step t, else 0), the consumer decides whether or not to continue browsing the $(t+1)$th product. If the consumer decides to continue browsing, partial information on $(t+1)$th product is revealed, $\mathbf{Z}_{t+1}$, the consumer incurs a browsing 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. We present the browsing model in Section 3.1.3.

3. **Purchase (Choice)**
   Once the search process terminates, the consumer has a final consideration set that consists of the items whose product detail pages have been clicked and the outside option of non-purchase. The consumer rationally chooses the highest utility alternative in the consideration set. See Section 3.1.1.

We explicate each step of the purchase funnel - first the utility function related to choice (purchase) is specified, then clicking and browsing decisions are explained. The existence and the uniqueness of the consumer model is detailed in online Appendix B.2.[22]

3.1.1 Purchase (Choice)

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

$$\begin{aligned} u_{ij} &= \mathbf{X}_j \alpha + \mathbf{Z}_j \beta + \epsilon_{ij} \\ u_{i0} &= \epsilon_{i0} \end{aligned} \tag{1}$$

[22]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. Another approach might be using a reduced-form aggregate consumer model. Such a demand system is not policy-invariant owing to its lack of structural foundations. For example, the price elasticity estimated under the current setting will differ from that when items are sorted by price. Given our emphasis on counterfactual analyses of changing the ranking (and changing the fees, which ultimately affects the ranking), this is a major limitation in using an aggregate demand system.

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 browses through the product list, some product characteristics are accessible without retrieving the product detail page. 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 clicked. 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 'consideration set' is defined as the set of items whose product detail pages have been visited (clicked). The outside good (not purchasing) does not require a search, and is available in the consideration set from the beginning at no cost. The outside good can be construed to capture the option value of shopping in other stores on the site, or leaving the site without a purchase (e.g., the option value of shopping for the good elsewhere).

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, d_i^p indicates whether item j is chosen by consumer i.

3.1.2 Clicking Decision

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

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

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

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

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

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 click 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 click decision. This error term is distinguished from the match value $\epsilon_{ij(t)}$, which is revealed inside the product detail page after clicking.

Clicking Benefits Recall that 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 click, the consumer makes the click decision based on beliefs about whether adding the current item to the consideration set will yield higher utility than previously clicked 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 click, 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 set from the beginning, so $u^*_{i0} = u_{i0}$. Using this notation, the conditional value function of the click decision is given by the sum of the current period utility ($-c^c$ if click, and 0 if not click) and the future utility flows accruing from the click decision, net of the choice specific error $\eta^c_{d^c it}$, that is:

$$\begin{aligned} v^c_0(u^*_{it-1}, \mathbf{Z}_{j(t)}) &= \int_{u^*_{it}} Emax^{browse}\left(u^*_{it}, \mathbf{Z}_{j(t)}\right) f^c_0\left(u^*_{it} \mid u^*_{it-1}, \mathbf{Z}_{j(t)}\right) \\ v^c_1(u^*_{it-1}, \mathbf{Z}_{j(t)}) &= -c^c + \int_{u^*_{it}} Emax^{browse}\left(u^*_{it}, \mathbf{Z}_{j(t)}\right) f^c_1\left(u^*_{it} \mid u^*_{it-1}, \mathbf{Z}_{j(t)}\right) \end{aligned} \tag{2}$$

where the future utility flows after clicking an item involve the expected value that will accrue from the next browsing decision (see Figure 7), or

$$
\begin{aligned}
Emax^{browse}\left(u_{it}^{*},\mathbf{Z}_{j(t)}\right) &= E_{\eta_0,\eta_1}\left[\max\ \left\{v_0^{s}\left(u_{it}^{*},\mathbf{Z}_{j(t)}\right)+\eta_{0it}^{s},\ v_1^{s}\left(u_{it}^{*},\mathbf{Z}_{j(t)}\right)+\eta_{1it}^{s}\right\}\right] \\
&= ln\left[exp\left(v_0^{s}\left(u_{it}^{*},\mathbf{Z}_{j(t)}\right)\right)+exp\left(v_1^{s}\left(u_{it}^{*},\mathbf{Z}_{j(t)}\right)\right)\right]+\kappa
\end{aligned} \tag{3}
$$

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

The first line in equation (2) captures the value of not clicking, v_0^c, and the second line captures the value of clicking, v_1^c. Functions 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. The online Appendix B.1 derives the state transitions, f^c, on these beliefs.

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

Clicking Decision Given the choice specific value functions above, the conditional choice probability of no click, $d^c=0$, 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 (Arcidiacono and Miller 2011). Once the click decision is made at position t, a consumer proceeds to browse decision and decides whether they want to terminate or continue to browse $(t+1)$th item.

3.1.3 Browsing Decision

Analogous to click, consumers will browse as long as the expected benefit of doing so exceeds the cost.

Browsing Costs Browsing cost c^s are specified as

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

Browsing Benefits Once u_{it}^* is revealed based on the click decision ($u_{it}^*=u_{it-1}^*$if t-th position product is not clicked), the consumer must then decide whether or not to browse 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 browse decision is

$$U^s_{d^sit} = \begin{cases} u^*_{it} + \eta^s_{0it} & \text{if browsing stops, } d^s = 0 \\ -c^s + \eta^s_{1it} & \text{if browsing continues, } d^s = 1 \end{cases} \tag{5}$$

where $\eta^s_{d^sit}$ is assumed to follow iid Type I Extreme Value (Gumbel) distribution. The first line in equation (5) indicates that a consumer who stops browsing at step t will receive utility u^*_{it} (reflective of the best alternative found prior to stopping browsing) plus a random shock observed by the consumer but not the researcher. This alternative-specific shock might include unobserved factors such as internet connectivity, incoming online messages from a friend, or general time constraints that affect browsing behavior. Alternatively, if a consumer continues to browse, he will pay a browsing 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 browsing. The conditional value function for the browse decision at position t, that is the sum of the current period utility ($-c^s$ if browsing is continued, and u^*_{it} if browsing is stopped) and the future utility flows accruing from the browse decision, net of the browsing choice specific error $\eta^s_{d^sit}$, can be written as

$$\begin{aligned} v^s_0(u^*_{it}, \mathbf{Z}_{j(t)}) &= u^*_{it} \\ v^s_1(u^*_{it}, \mathbf{Z}_{j(t)}) &= -c^s + \int_{\mathbf{Z}_{j(t+1)}} Emax^{click}\left(u^*_{it}, \mathbf{Z}_{j(t+1)}\right) f^s_1\left(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}\right) \end{aligned} \tag{6}$$

where

$$\begin{aligned} Emax^{click}\left(u^*_{it}, \mathbf{Z}_{j(t+1)}\right) &= E\left[\max\ \left\{v^c_0\left(u^*_{it}, \mathbf{Z}_{j(t+1)}\right) + \eta^c_{0i(t+1)},\ v^c_1\left(u^*_{it}, \mathbf{Z}_{j(t+1)}\right) + \eta^c_{1i(t+1)}\right\}\right] \\ &= ln\left(exp\left(v^c_0\left(u^*_{it}, \mathbf{Z}_{j(t+1)}\right)\right) + exp\left(v^c_1\left(u^*_{it}, \mathbf{Z}_{j(t+1)}\right)\right)\right) + \kappa \end{aligned} \tag{7}$$

$f^s_1\left(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}\right)$ is the distribution of consumers' beliefs on future $\mathbf{Z}_{j(t+1)}$ conditional on the decision to continue browsing (see online Appendix B.1). The continuation value of browsing is given in the second line of equation (6), and corresponds to the expected maximum of the utility of the ensuing click decision, as the continuation of browsing 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 browse decision and following click decision for $(t+1)$th product is short. Though we discuss product attribute state transitions $f^s_1\left(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}\right)$ in online Appendix B.1, it is worth noting that the browse decision can be informative about click if the attributes on the product listing page $\mathbf{Z}_t$, are correlated with the attributes inside the product detail page $\mathbf{X}_t$.

Browsing Decision Note that *stop browsing* is a terminal decision that ends the search process altogether. With the double exponential parametric assumption on $\eta^s_{d^sit}$, the conditional choice probability of ending browsing, $d^s = 0$, is given by

$$p_0^s\left(u_{it}^*, \mathbf{Z}_{j(t)}\right) = \frac{1}{1 + exp\left(v_1^s\left(u_{it}^*, \mathbf{Z}_{j(t)}\right) - v_0^s\left(u_{it}^*, \mathbf{Z}_{j(t)}\right)\right)} \tag{8}$$

If we denote *stop browsing* 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 Γ_{iT^s}. This payoff related to purchase is embedded in the browse 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 positions, thereby increasing exposures and potentially clicks and purchases, which in turn increase 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 browsing, clicking, and purchasing*, 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, clicks, and browses 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, click, and browse (impression) responses based on the distribution of consumer preferences and costs from consumer model:

$$\widehat{D_{j,d_j^a \mathbf{d_{-j}^a}}} = D\left(\widehat{Rank_{j,d_j^a \mathbf{d_{-j}^a}}}, \mathbf{X}, \mathbf{Z}\right); \; \widehat{C_{j,d_j^a \mathbf{d_{-j}^a}}} = C\left(\widehat{Rank_{j,d_j^a \mathbf{d_{-j}^a}}}, \mathbf{X}, \mathbf{Z}\right); \; \widehat{I_{j,d_j^a \mathbf{d_{-j}^a}}} = I\left(\widehat{Rank_{j,d_j^a \mathbf{d_{-j}^a}}}, \mathbf{X}, \mathbf{Z}\right) \tag{9}$$

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. 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 the 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.[23]

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,cost-per-mille, and auction mechanism in the advertiser model as part of our policy simulations.

[23]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)

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). Building on Chan and Park 2015, we model sellers as gaining valuations from three sources: (i) demand, (ii) clicks, and (iii) impressions (browsing). Impressions and clicks can generate value from, for example, creating value via branding. Specifically, seller k's valuation for product j from advertising decision d_j^a is

$$\pi_{jkd^a} = \theta \cdot \mathbf{w}_{jk} \cdot \mathbf{1}(d^a = 1) + \pi^D_{jd^a} + \pi^C_{jd^a} + \pi^I_{jd^a}$$

where $\pi^D_{jd^a}$, $\pi^C_{jd^a}$, $\pi^I_{jd^a}$ are valuations from demand, clicks, and impressions respectively. To accommodate product-seller level heterogeneity and to control for the remaining effect of observable characteristics on advertising beyond what the consumer 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. The unobserved heterogeneity at the product level is captured by the structural error term ξ_j, which is assumed to follow a normal distribution. The seller advertises product j if doing so is profitable, that is if the below condition is satisfied.

$$\begin{aligned} \left(\theta \cdot \mathbf{w}_{jk} + \pi^D_{j1} + \pi^C_{j1} + \pi^I_{j1}\right) + \xi_j &\geq \left(\pi^D_{j0} + \pi^C_{j0} + \pi^I_{j0}\right) \\ \xi_j &\sim N(0, \sigma^2_\xi) \end{aligned} \tag{10}$$

Valuations from 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 demand is represented as

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

$$\delta_j \sim N(\delta, \sigma^2_\delta)$$

where D_{jd^a} and p_j are demand and price for product j respectively. The parameters δ and σ^2_δ represent the mean and the variance of the underlying marginal cost distribution and captures the product level unobserved heterogeneity in marginal cost. θ^D is a scale parameter that maps seller's short-term profits valuations.[24] For the same marginal costs, higher f^T or f^A implies that the seller has a greater incentive to redirect consumer to the outside channels for purchase.

[24] 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).

Valuations from Clicking and Browsing (Impressions) The other two components of the advertiser's valuation come from clicks and impressions. The seller gains benefit from clicks and impressions, 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 that 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 sale, either through branding or future sales.[25]

We assume that the seller's valuation from clicks and impressions 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 overexposure.[26] The valuation from clicks and impressions are given by

$$\begin{aligned} \pi^C_{jd^a} &= \theta^C log\left(C_{jd^a}\right) - f^C C_{jd^a} \\ \pi^I_{jd^a} &= \theta^I log\left(I_{jd^a}\right) - f^I I_{jd^a} \end{aligned} \tag{12}$$

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

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

$$p^a_{jk1} = \Phi\left[\frac{\left(\theta\cdot\mathbf{w}_{jk} + \psi^D_{j1} + \pi^C_{j1} + \pi^I_{j1}\right) - \left(\psi^D_{j0} + \pi^C_{j0} + \pi^I_{j0}\right)}{\sqrt{\sigma^2_\delta p_j\left(D_{j1} - D_{j0}\right) + \sigma^2_\xi}}\right] \tag{13}$$

where $\psi^D_{jd^a} = \theta^D(1 - f^T - f^A\mathbf{1}(d^a_j = 1))D_{jd^a}p_j$.

[25] 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.

[26] In Figure 3, as #browses (and #clicks) decrease exponentially with position, firms with products ranked closer to the top will have a much higher increase in #impressions and #clicks from advertising (e.g., going from position 10 to 1 will yield a much higher increase in #impressions and #clicks than going from position 1000 to 990). Were advertiser valuations linear in impressions and clicks, advertisers organically positioned higher would advertise more because they gain more #impressions and #clicks from advertising. However, we find the opposite holds (Figure 5), suggesting marginally decreasing returns from clicks and impressions. Based on this rationale, we accommodate diminishing marginal returns in our advertiser valuation model.

4 Estimation

In this section we outline our estimation approach to the consumer model and the advertiser model. The goal of the consumer model is to infer preferences and browsing/clicking costs, and the goal of the advertiser model is to infer advertiser valuations for impressions, clicks, and purchases.

4.1 The Consumer Model

In this sub-section we develop the consumer model likelihood and overview identification.

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 upon browsing an item (but before clicking it) includes seller identity, price, and the number of likes (μ_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 browsed have zero demand and zero clicks 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 unobservables.[27]

4.1.2 Likelihood and Heterogeneity

The log-likelihood of browsing, clicking, 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 $\lambda^1, ..., \lambda^G$ represents the type probability of each segment when there are G latent classes (Kamakura and Russell 1989).

Let T_i^s reference the position where individual i chooses to stop browsing such that $d^s_{iT_i^s} = 0$. The likelihood of observing $\mathbf{d}_i = \{d^c_{i1}, ..., d^c_{iT_i^s}, d^s_{i1}, ..., d^s_{iT_i^s}, d^p_{i1}, ..., d^p_{iT_i^s}\}$ for individual

[27]The inclusion of category-seller level unobservables and exclusion of product level unobservables is motivated by data limitation and not by 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).

i in latent class g is defined as

$$
\begin{aligned}
L_i(\Theta_1^g) &= \int_{u^*_{iT_i^s}} ... \int_{u^*_{i1}} \int_{u^*_{i0}} f^u\left(u^*_{i0}\right) \mathcal{L}(\mathbf{d}_i \mid u^*_{i0}, ..., u^*_{iT_i^s}, \mathbf{Z}, \mathbf{X}; \Theta_1^g) \\
&= \int_{u^*_{iT_i^s}} ... \int_{u^*_{i1}} \int_{u^*_{i0}} f^u\left(u^*_{i0}\right) \prod_{t=1}^{T_i^s} \mathcal{L}_t^{browse} \mathcal{L}_t^{click|browse} \mathcal{L}_t^{purchase|browse,click} \qquad (14)
\end{aligned}
$$

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

$$
L(\Theta_1) = \sum_{i=1}^{I} ln \left(\sum_{g=1}^{G} \lambda^g L_i(\Theta_1^g) \right) \qquad (15)
$$

where we integrate out latent class consumer heterogeneity. In online Appendix C.1.1, we derive the joint likelihood of browsing, clicking, and purchase. Of note, the likelihood function is not separable and the state transition, $f^u\left(u^*_{it} \mid u^*_{it-1}, \mathbf{Z}_{j(t)}, \mathbf{X}_{j(t)}\right)$, links $\mathcal{L}_t$ and $\mathcal{L}_{t-1}$.

4.1.3 Solving the Dynamic Problem

We formulate the consumer model as an infinite horizon problem. We maximize the joint likelihood 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

Our identification discussion covers four domains - the identification of costs, preferences, heterogeneity, and the discussion on the error terms.

Search Costs Browsing costs are identified from the variation in the number of items browsed with respect to the (exogenous) variation on slot positions conditioned on the product characteristics. The clicking cost is separately identified from the browsing cost based on variation in how many products consumers click, conditioned on the browsing length and product characteristics.

Preferences The identification of the utility parameters comes from the consumers' browsing/clicking decisions and the purchase decisions. As we observe purchase directly, identification of the preference parameters is standard, as in a conditional choice model. Additionally, observing consumers' browsing and clicking behaviors strengthens identifiability of the preference parameters because the selection of which product characteristics to click (in addition to how many) helps to pin down the preference parameters.(see Chen and Yao

2014, Kim et al. 2015, Honka et al. 2017). For example, given a fixed browsing length, clicking on more low-price items implies greater price sensitivity. Online Appendix C.1.3 reports simulation results suggesting the inclusion of purchase data significantly reduces the standard errors of the parameter estimates over browsing/clicking data alone, especially for the preference parameters.

Heterogeneity In our empirical application, most consumers' visits are highly episodic (with median 2 visits per individual), thus we use a finite mixture model assumption to help identify heterogeneity in costs.

Structural Errors

1. **Match Value**: The normal distribution on the match value, ε, follows the commonly adopted distributional assumption in existing Weitzman-type search models (e.g., Kim et al. 2010, Chen and Yao 2014). The variance of match error term (ϵ) is normalized be $\sigma_\epsilon^2 = 1$ for identification purposes.

2. **Structural Error for Clicking**: The introduction of the the structural error term for clicking ($\eta^c_{d^c it}$, known to consumer *prior* to clicking), separately from the match value for clicking (ε, revealed *after* clicking an item), accommodates the possibility that consumers purchase even the non-terminal clicked items.[28] Following the dynamic discrete choice model literature (Arcidiacono and Miller 2011), the structural error term for clicks ($\eta^c_{d^c it}$) is assumed to follow T1EV distribution, and the scale is normalized to 1 for identification. With this T1EV distributional assumption, the value functions in equation (7) has a closed-form, which greatly reduces the computational complexity associated with estimation.[29]

3. **Structural Error for Browsing**: A separate error term for browsing ($\eta^s_{d^s it}$) is required to accommodate the possibility consumers browse extensively after the last click.[30] Similarly to the structural error term for clicking, the structural error term for browsing

[28] In a Weitzman-type model where a single utility function error term (ε, match value) is used, the optimal strategy is to purchase the last clicked item (e.g., the no recall test in De los Santos et al. 2012) under constant search costs. However in our data, the percentage of purchases where the purchased item is not the last clicked item is 33%.

[29] An example of an $\eta^c_{d^c it}$ would be an especially attractive image revealed upon browsing, but before clicking. In contrast, aspects pertaining to feature/product descriptions within the product detail page are observed by the consumer only after clicking the item, exemplify the match value (ε). A similar discussion on the difference between the match value term (ε) and the classic structural error terms ($\eta^c_{d^c it}$) can also be found in footnote 24, Honka 2013.

[30] In our data, the last click rarely coincides with the last browse. The percentage of visits with consumers browsing >10 more items even after the last click is 96%.

is assumed to follow T1EV with scale 1.[31]

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, clicks, 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 his/her 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.

$$\widehat{Rank}_{j,t,d_j^a,\mathbf{d}_{-j}^a} = g\left(d_j^a,\ E_t(\mathbf{d}_{-j,}^a),\ J_t,\ \text{Days Listed}_{jt},\ \text{Organic Strength}_j\right) \tag{16}$$

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).[32] 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, clicks, 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, click, and impression responses (equation (9)). That is, sellers form expectations by integrating out over the belief distribution of product ranks and consumer behaviors. As we formulate the advertiser model in a static framework, expected impressions, clicks, and demand are imputed over the duration of the product listing (i.e., net present value of impressions, clicks, and purchases). Using the consumer demand model, consumer responses are 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

[31] See Seiler 2013 p.183 for a similar discussion, where separate set of T1EV error terms are introduced for each decision stage in order to obtain an analytic solution for the value functions.

[32] To validate this assumption, we show that the actual ranking by the platform's algorithm and the approximate ranking based on equation (16) 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)

periods.

4.2.2 Likelihood

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

$$\mathcal{L}^a_{jk}(d^a_{jk};\Theta_2) = {p^a_{jk1}}^{1(d^a_{jk}=1)} \times \big[1 - p^a_{jk1}\big]^{1(d^a_{jk}=0)}$$

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

$$L^a(\Theta_2) = \sum_{j=1}^{J} ln\, \left(\mathcal{L}^a_{jk}(d^a_{jk};\Theta_2)\right) \tag{17}$$

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 (16). In stage 2, sellers' beliefs on product placement and consumer responses with respect to advertising are constructed. By contrasting the valuation from demand, click, and impression responses when advertising and when not advertising, the seller's advertising probability is imputed. The parameters in interest, $\Theta_2 = \big(\theta,\, \theta^D,\, \theta^C,\, \theta^I,\, \delta\big)$, are then recovered in stage 3 using maximum likelihood estimation method based on the likelihood function in equation (17). 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 in the advertiser model, the advertiser valuations for demand, clicks, and impressions 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:

$$\begin{aligned}\pi_{jk1} - \pi_{jk0} = \theta \cdot \mathbf{w}_{jk} &+ \theta^D(1 - f^T - \delta)p_j\,(D_{j1} - D_{j0}) \\ &+ \theta^C\,(log\,(C_{j1}) - log\,(C_{j0})) - f^C\,(C_{j1} - C_{j0}) \\ &+ \theta^I\,(log\,(I_{j1}) - log\,(I_{j0})) - f^I\,(I_{j1} - I_{j0}) \\ &- \theta^D f^A p_j D_{j1}\end{aligned} \tag{18}$$

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 clicks and impressions are recovered from the increase in clicks and impressions via advertising. If an increase in clicks (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

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' browsing, clicking, and purchase behaviors. Both the browsing and clicking costs significantly affect the length and depth of search and the formation of the consideration set. The second column in Table 5 reports the results from a two segment model where the heterogeneity is imposed on both preference and cost. The third to fifth columns report results from the model with two to four segments where the heterogeneity is imposed only on the cost parameters. The four-segment model with heterogeneity on the cost parameters yields the best result in terms of the Bayesian information criterion (BIC).[33] About 71% of the consumers belong to the group with the browsing cost estimate of 0.17 and the clicking cost estimate of 1.76. About 20% (4%) of the consumers browse considerably more (less), but click less (more), and about 5% of the consumers browse and click more than the majority. The average marginal cost of browsing and clicking are \$0.89 and \$3.90 respectively, but there exists considerable heterogeneity (ranging in \$0.87 – \$0.92 for browsing and \$2.39 – \$4.41 for clicking costs).[34] In-sample and out-of-sample model fits are reported in Table 15 in online Appendix.[35]

[33] The BIC of the five segment model is 18377.

[34] Chen and Yao 2014 report a click cost of about 13% of the average hotel price (= \$21.54/\$169), and a marginal browsing cost (as inferred from the slot coefficient in their model) of about \$1.01 (= $exp(0.01)$). In our case, the marginal click cost is about 20% of the average product price (= \$3.90/\$19.5) and the marginal browsing cost is \$0.89. These numbers are quite close, with the differences reflecting many browses and smaller clicks observed in our data (i.e., average clicks are 0.8 in our data as compared to 2.3 in Chen and Yao 2014).

[35] We test an alternative model wherein search is modeled myopically (i.e., the discount factor is set to 0 at the browsing decision step, implying that consumers search aimlessly). The myopic model fit deteriorates markedly with substantially lower log-likelihood (−14443), suggesting that consumers are forward looking and pay search costs in return for future gains.

Table 5: The Consumer Model Estimates

Parameter		1 Segment	2 Segments	2 Segments on costs	3 Segments on costs	4 Segments on costs
Preference						
Type1	# Pictures (X)	**0.20** (0.11)	0.09 (0.15)	0.18 (0.15)	**0.18** (0.09)	**0.18** (0.10)
	Log (Price) (Z)	−**0.25**(0.15)	−0.11(0.22)	−**0.24**(0.14)	−**0.25**(0.15)	−**0.29**(0.15)
	# Likes (Z)	−0.00(0.01)	−0.00(0.01)	−0.00(0.01)	−0.00(0.01)	−0.00(0.01)
	Constant	−**3.05**(0.61)	−**2.86**(0.80)	−**2.84**(0.87)	−**2.77**(0.24)	−**2.67**(0.61)
Type2	# Pictures (X)		**0.27** (0.15)			
	Log (Price) (Z)		−**0.37**(0.22)			
	# Likes (Z)		−0.01(0.02)			
	Constant		−**2.79**(0.84)			
Cost						
Type1	Clicking	**1.52** (0.01)	**1.48** (0.01)	**1.48** (0.01)	**1.37** (0.02)	**1.42** (0.02)
	Browsing	**0.16** (0.00)	**0.18** (0.00)	**0.18** (0.00)	**0.16** (0.00)	**0.16** (0.00)
Type2	Clicking		**1.55** (0.01)	**1.55** (0.01)	**1.75** (0.03)	**1.77** (0.03)
	Browsing		**0.15** (0.00)	**0.15** (0.00)	**0.15** (0.00)	**0.15** (0.00)
Type3	Clicking				**1.52** (0.02)	**1.16** (0.04)
	Browsing				**0.18** (0.00)	**0.20** (0.00)
Type4	Clicking					**1.76** (0.05)
	Browsing					**0.17** (0.00)
Segments						
	Pr(Type1)		**0.91** (0.04)	**0.91** (0.04)	**0.05** (0.01)	**0.05** (0.01)
	Pr(Type2)				**0.06** (0.01)	**0.04** (0.01)
	Pr(Type3)					**0.20** (0.04)
LL ($N = 74400$)		−9657.56	−9244.66	−9245.83	−9147.45	−9076.56
BIC		19404.9	18657.58	18615.04	18451.95	18343.80

5.1 The Advertiser Model

Table 6 details the estimates from the advertiser model. Via taking log on click and impression (browsing), 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' browsing, clicking, and demand responses. For example, consumers' behavior is not found to be responsive to different materials the products are made 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 product.

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

Table 6: The Advertiser Model Estimates

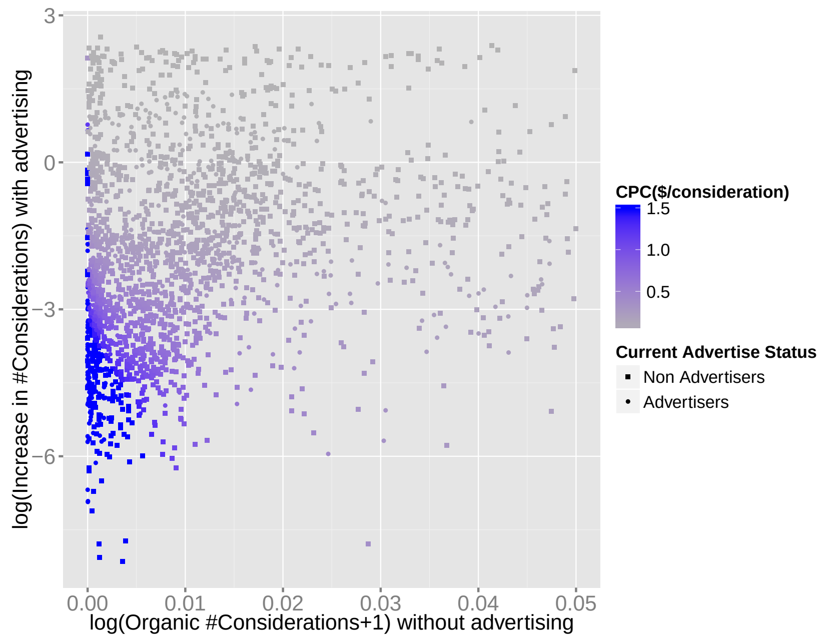
	Parameter	Estimates
θ^D	Demand	**0.62** (0.37)
θ^C	log(Clicks)	**0.017** (0.005)
θ_1^I	log(Impressions (in thousand))	0.000 (0.000)
δ	Marginal Cost Mean	**0.74** (0.03)
σ_δ	Marginal Cost SD	**0.007** (0.06)
θ	Constant	$-$**1.01** (0.06)
	Brand Group 1 (# product listing > 150)	$-$**1.68** (0.16)
	Brand Group 2 ($85 <$# product listing≤ 150)	$-$**0.35** (0.06)
	Include URL	**0.28** (0.06)
	Silver	**0.44** (0.15)
	Stone	**0.20** (0.09)
	Bracelet	**0.29** (0.07)
	Refundable	**0.26** (0.06)
	LL ($N = 2853$)	-1263.7

Negative valuation from demand if advertised: $(1 - f^T - f^A - \delta) = -0.04$

δ, which captures the marginal cost. As 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 ($100-17\%-13\%-74\% = -4\%$ 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 clicks from advertising on the y-axis and the number of logged clicks 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 (click) 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 clicks in the absence of advertising have higher valuations from a unit increase in click (darker color dots), and are more likely to advertise. In other words, the first few clicks generate the largest valuations to advertisers. The quantiles for average value per click are \$0.04 (25%), \$0.13 (50%), \$0.48 (75%). The average conversion rate (#total demand/#total clicks) in our data is 5%, so the cost per conversion is calculated to

Figure 8: Valuations from Consideration (Click)



Avg value per consideration quantiles: \$0.04 (25%), \$0.13 (50%), \$0.48 (75%)

be \$2.6. As the median price is \$14, the total willingness to pay for clicks is about 18.6% of the transaction amount.[36] While the results suggest advertisers accrue valuations from clicks beyond valuations from purchases, we find that advertisers rarely gain valuations from impressions. This is consistent with the findings in Chan and Park 2015, where the value per impression is found to be 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, we explore how product ranking decisions (e.g., sorting by consumers' utility, price, past sales, or expected revenue) affect consumers' browsing (impressions), consideration (clicking), and choice (purchase) of merchant goods. On the supply side, we explore how payment mechanisms (CPM, CPC, CPA) and ranking rules together affect consumer and advertiser behaviors and welfare. We detail these policy analyses below.

[36]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 a typical retail price of \$22, and our click valuation is consistent with their findings.

6.1 Simulation Procedures

Details on the policy simulation procedures are included in online Appendix C.2.3. Of note here, we update consumers' beliefs (state transitions) in simulations 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. For example, if the ranking algorithm changes, consumers' beliefs about the characteristics of the next product to be potentially considered should also change.

For the consumer model simulations, we do not consider advertisers' responses, as our goal is to ascertain how consumer behaviors change, all else fixed. For the advertiser model simulations, we update sellers' beliefs as well with respect to the changes in ranking and fee structure. Specifically, we construct sellers' new beliefs on their own position per equation (16) under the counterfactual. One advantage of the structural approach over a simpler model is that it explicitly captures changes in consumer and advertiser beliefs. Lastly, changing the ranking or the fee structure may affect sellers' listing behavior (i.e., a seller will unlist an item if the expected fees are higher than the expected gains). To account for the change in the seller's listing behavior, we impose a participation constraint for the advertiser model simulations that each seller's utility is greater than the minimum of the seller utilities estimated in the actual fee structure setting in each iteration step. Those who gain lower than this threshold are assumed to drop out (delist items).

6.2 Consumer Model Simulations

6.2.1 The Effect of the Marketplace Ranking Algorithm on Browsing, Clicking, Purchase

While featuring advertised products generates advertising revenue, it can also impede search, thereby reducing transaction commissions. This leads to a trade-off between advertising revenue and sales commissions that can be considered using our model. Hence, we contrast the current ranking scheme with one that orders products by (i) utility level, (ii) price (from lowest to highest), (iii) past sales (volume), and (iv) expected revenue (i.e., expected item demand $\times$ item price).[37] In each simulation, we first measure consumer responses, then revenue implications for the platform.

Table 7 suggests that ranking goods by consumer preference, price, or past sales volume

[37]When ordering products by utility level, the available (listed) products are sorted by the choice utility (consumption utility) in equation (1) based on the consumer model estimates. 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 the individual consumer.

Table 7: Consumer Response

Consumer Response (% Change)	Ranking Rule			
	Utility	Price	Past Sales	Revenue
Browsing	−1.98	0.68	−0.53	−0.42
Clicking	−1.4	1.07	−0.21	−0.89
Purchase (Volume)	119.8	35.4	13.8	−2.49
Avg. Price Purchased	−58.4	−86.3	−4.66	207
Total Search Costs (Browsing + Clicking)	−1.97	0.71	−0.52	−0.44
Choice Utility	164.9	56.6	14.6	−1.51
Overall Utility	2.04	−0.68	0.53	0.44

generates increased consumption utility, u_{ij}, relative to the the current ranking algorithm that favors advertised goods in the rankings. Specifically, consumers' choice utility increases by (165%, 57%, 15%) and the number of items sold by (120%, 35%, 14%) when sorting by utility, price, and past sales volume, respectively. On the other hand, sorting by expected revenue decreases both the number of items sold and the consumers' choice utility.

Sorting products by preferences has two countervailing effects on search behavior. On the one hand, consumers may browse/click less if they find the best item early in the search process. On the other hand, consumers may browse/click more if the expected future benefit is high. When products are sorted by consumers' utility, the former effect dominates, as consumers' browsing (clicking) decreases by 2% (1%). Combined, the effect of decreased search costs (browsing and clicking costs) from finding the preferred item sooner and the increase in choice utility from finding a better item leads to an overall utility increases of 2% when sorting by utility.[38]

Though sorting products by consumer preferences can increase consumer welfare (and potentially transaction commissions), it can also lower revenue from advertising (i.e., sellers have no incentive to pay for advertising, as there is no increase in rank position from advertising). Table 8 highlights this trade-off. Reordering items by consumer's utility or price decreases the commissions from transactions. This result is mainly driven by the fact that consumers are price sensitive and purchase lower-price items displayed earlier in the

[38]In Chen and Yao 2014, the average utility of hotels booked increases by 17% with the refinement tool (sorting/filtering) as compared to without one. The larger percentage gains in choice utility (165%, 57%, 15%) in our context arise from the default ranking system, which does not emphasize consumer preferences in the scoring algorithm. The (baseline) default ranking is predominantly influenced by "days listed (i.e., sorting by newest to oldest, Figure 2), followed by advertising and popularity scores. As a result, consumer utility is relatively low to start, enabling large potential gains. In contrast, Chen and Yao 2014 mention that *"the default ranking of hotels is based on booking frequencies, which to some extent already reflects the average utility levels of these hotels among population. Consequently, even without refinement tools, the baseline level of consumer welfare is fairly high if consumers make decision according to the default ranking."*

product list; the increase in sales volume is not large enough to offset the decrease in the transaction commissions. As such, sorting by consumer's utility or price neither increases transaction revenues nor advertising revenues.

When sorting products by past sales volume, the increase in transaction commissions also does not offset the decrease in advertising commissions.[39] Accordingly, platform's profits decrease by 10% when sorting by past sales. Our analysis provides one insight regarding why many online marketplaces collect advertising fees and do not display items purely organically (i.e., by consumer's utility, price, or past sales) as a default ranking mechanism.

Sorting by expected revenue (i.e., expected demand × price), on the other hand, increases platform's profits as the increase in transaction commissions is greater than the decrease in advertising commissions. This result suggests that the ranking algorithm (and fee structure) currently in place is sub-optimal, thus motivating the next question; how can the online marketplace better balance the trade-off between commissions and ad fees by changing the ranking algorithm and fee structure in a manner that accounts for both consumers' and advertisers' responses. We address this question next.[40]

Table 8: Effect of Ranking Strategy on Platform Profits

Platform Profits (% Change)	**Ranking Rule**			
	Utility	Price	Past Sales	Revenue
Commissions from Transactions (f^T)	−	−	+	+
Commissions from Advertising (f^A)	−	−	−	−
Overall Platform Profits	−24.0	−84.6	−9.8	148.5

6.3 Advertiser Model Simulations

To assess how changes in the ranking algorithm and fee structure affect consumers' and advertisers' behaviors and the marketplace's profits, we conduct 4 simulations: (i) changing the product ranking algorithm in isolation; (ii) changing fee structure in isolation; (iii) changing both the ranking algorithm and fee structure together via auctions on clicks (CPC) coupled with displaying products by (expected clicks × bids); and (iv) conducting auctions on clicks (CPC) in only the top 5 positions (i.e., limiting advertising slots) and changing the ranking algorithm to sort by expected revenue (i.e., expected demand × price) in slots

[39]Note that past sales are not only correlated with consumers utility, but also with sellers' advertising decisions and the platform's ranking algorithm in the past. Therefore, the results for sorting by past sales can differ from sorting by utility.

[40]In calculating the platform's profits for the counterfactual setting, we set $f^A = 0$ as advertising has no effect on ranking.

6+. Counterfactual (i) focuses on rankings, counterfactual (ii) focuses on pricing mechanism, counterfactuals (iii-iv) consider both.

6.3.1 The Effect of Increased Advertising Weight in the Marketplace Ranking Algorithm

Increasing the weight of advertising in the product ranking algorithm will provide a greater incentive to advertise. This yields greater advertising revenue. On the other hand, to the extend the advertised goods do not align with preferences, advertising is more likely to disrupt search, thus yielding lower revenue from transactions. To explore this trade-off, we consider the case where the position of an advertised product is improved by 10% over the current policy by adjusting the weight in the ranking algorithm (which converts to a median increase of about 200 slots).

Consistent with a ranking algorithm that makes advertising more effective by increasing the lift in rank for advertised products, the mean advertising probability increases by 3%. 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 competitive response. Further, as competition intensifies, seller welfare falls 7.3%, reinforcing the importance of capturing competition in the advertiser model. Overall, the increase in advertiser spending generates more revenue for the marketplace.

On the consumer side, however, consumers' browsing lengths, clicks, and purchases decrease by 0.3%, 0.5%, and 5% respectively, and their ex-post consumption utility lessens by 3.2%. This negative effect on consumption utility can be explained by the finding that organically weaker (less popular) products have higher marginal valuation for advertising, and sellers are more prone to advertise these goods. In this regard, heavier weight on advertising disrupts consumers' search processes as the likelihood of finding goods they want within their browsing 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 3.5% due to this increase in commissions from advertising. In contrast, sellers' overall welfare decreases by 7.3% as they face higher advertising competition and pay more for advertising commissions.

6.3.2 The Effect of the Marketplace Fee Structure: Combining CPA and CPC

As various fee structures differentially affect each stage of the purchase funnel (impressions, clicks and purchases), a question of general interest is which pricing mechanism should be

Table 9: Effect of Platform Strategies on Consumers and Advertisers

		Advertiser Side Policy			
Policy	Ranking Rule	+10%	–	Auction Revenue	Hybrid
Manipulation	Fee	–	$f_c' = 0.35$	CPC Auction	5 Positions
Response	**Consumer**				
(% Change)	Browsing	−0.3	0.7	−0.9	−0.3
	Clicking	−0.5	3.6	−0.9	−0.26
	Purchase (Volume)	−5.0	5.3	17.7	6.8
	Choice Utility	−3.2	7.2	24.8	15.0
	Advertiser				
	Prob (Ad)	2.6	−11.2	–	–
	Seller Welfare	−7.3	2.8	−8.7	−399
	Platform				
	Profits	3.5	156	177	181

used by the online marketplace platform. Hence, we first explore the implication of a fixed cost-per-click (CPC) basis, and a percentage of the sale basis (cost-per-action or CPA) as a next counterfactual analysis, keeping the current ranking algorithm.[41]

To find the (pareto) optimal fee structure for this online marketplace platform, we conduct a coarse grid search combined with a steepest descent method on the profit objective function as a function of CPC and CPA fees. Findings are presented in the second column of Table 9. The optimal fee structure turns out to be setting zero cost-per-action (CPA) ($f_T = 0$, $f_A' = 0$) coupled with a more substantial \$0.35 charge for the click (CPC).[42] Although sellers are less likely to advertise (−11.2%), reducing CPA, and instead charging advertising fees based on CPC (and/or CPM) has the potential for pareto improvement leading to positive outcomes for both sellers and the platform. Sellers gain in overall welfare, as they do not face negative valuation on demand when advertising ($1 - f_T - f_A' - \delta = 1 - 0.13 - 0 - 0.76 = 0.11 > 0$). Intuitively, this finding suggests that the marginal fees of advertising ($f_A = 0.17$) are set too high under the current pricing scheme relative to the marginal gains from advertising and that advertiser valuations are better monetized via clicks.

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

[42] 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/)

6.3.3 The Effect of the Marketplace Fee Structure and Ranking: Auction on Clicks

A common advertising fee structure adopted in practice is the generalized second-price auction on clicks (Edelman et al. 2007). To explore the impact of such mechanism, we consider the following setting; the advertisers bid for clicks (CPC), and the platform ranks the products optimally by the rank score (i.e., expected clicks $\times$ bid). Advertising payment per click is set to be equal to (next highest rank score $\div$ expected clicks).[43] [44]

In the third column of Table 9, the platform profits increase, which is consistent with the theory that auction mechanisms can yield higher profits than the fixed pricing, especially when there are many bidders competing (Krishna 2009). Sellers are worse-off as the platform extracts more of the sellers' surpluses, whereas consumers are better-off as the platform integrates the expected clicks (reflecting consumers' preference) into the product ranking.

6.3.4 The Effect of the Marketplace Fee Structure and Ranking: Combining CPA and Auction on Clicks

CPC auctions leverage fees from advertising while foregoing the revenues from transactions. We conjecture that the platform outcome might be further improved if we combine an auction pricing mechanism with a different ranking policy. Thus, similar to Amazon's current practice, we explore an alternative that combines transaction commissions with a click auction.[45] Specifically, we simulate a generalized second-price auction on clicks for the top 5 slots while retaining a transaction commission level of ($f_T = 0.13$). The platform is assumed to rank the first 5 products by (expected clicks $\times$ bid) and by the expected revenue (expected demand $\times$ price) for the remaining list from slots 6 and lower (similar to sub-section 6.2). Note that this simulation is designed to enhance both transaction revenue and advertising revenue. Transaction revenue is enhanced by ranking slots 6 and lower, while advertising revenue comes from the sellers with the highest valuations for advertising.

The fourth column of Table 9 indicates that that platform's profits are the highest under this counterfactual, and that almost all of the sellers' surpluses are extracted by the platform, perhaps explaining the ubiquity of this "top slots" advertising mechanism in practice for online marketplaces. From this, we conclude that combining CPA and auction on clicks best

[43] Other fees are set to be zero ($f_T = 0,\ f_A = 0,\ f_I = 0$) in this exercise.

[44] Edelman et al. 2007 show that the total expected revenue to the seller under the generalized second-price auction is at least as high as in the dominant-strategy equilibrium of the Vickrey-Clarke-Grovew (VCG) auction. As our primary focus is on the seller's revenue, we look at the dominant-strategy equilibrium of the VCG in our counterfactual. For the valuation, we assume that the bid (truth-telling) equals the mean valuation (i.e., total expected valuation / total expected clicks).

[45] Amazon charges 15% of the transaction price in average as transaction commissions, and uses an auction-based CPC pricing model for the limited top slots.

balances the trade-off the platform faces between revenues from transactions and advertising. This strategy yields the largest profit gains for the platform.

7 Conclusion

This paper considers the monetization of online marketplaces. To achieve this aim, we consider all three agents in the two-sided network: i) the platform who sets the advertising fees (CPM, CPC, CPA) and placement of items listed on the market; ii) the sellers who jointly make advertising decisions conditioned on platform's policies and expected consumer behavior; iii) consumers who search (browse and click) and make purchase decisions given their preferences, search (browsing/clicking) costs, and the list of products displayed.

This research offers a number of advances with regard to the prior literature on consumer search and advertising in online environments. On the consumer side, our approach integrates browsing, clicking, and purchase behaviors in an online marketplace. On the seller side, we map each type of consumer engagement in the purchase funnel (browsing, clicking, and purchase) to the advertiser valuation thereof (CPM, CPC, CPA), and model the strategic interactions of advertisers in response to the platform's ranking algorithm and fee structure.

On the consumer side, we find that the information on price (external attribute) and the number of pictures (internal attribute) and both the clicking and browsing costs affect the length of search, formation of consideration set, and ultimately the products purchased by the consumers. The average marginal cost of browsing and clicking are \$0.89 and \$3.90 respectively, and there exists considerable heterogeneity across consumers.

On the seller side, we find that the combined marginal cost of goods and opportunity costs of selling elsewhere for the sellers on this platform is substantial (74% of the selling price). As a result, the valuation from unit demand is negative (-4% of the transaction amount) for the sellers who advertise. This negative valuation is due to the high CPA-based advertising fees that may incentivize sellers to redirect consumers to buy their product on other venues (or buy other seller products), and provides one seller-side explanation for the widespread "web-rooming" phenomenon. The median seller valuation from a click is estimated to be \$0.13, and sellers rarely gain positive valuations for impressions. In other words, sellers appear to value the potential for clicks more than selling an item on the marketplace, under the current fee structure.

On the platform side we consider two strategies - changing the ranking algorithm and changing the advertising pricing mechanism. A trade-off between ad revenue and sales revenue must be balanced in these strategies, as increased advertising can interrupt consumer search leading to lower sales. With regard to ranking strategy, ordering products by consumer utility or from low to high price increases items sold, but decreases platform profits as those items that are sold are lower-price items relative to the prices of goods sold under the current ranking algorithm. Although sorting by past sales increases transaction commissions, it decreases platform's profits due to the decrease in advertising fees. On the other hand, listing items by expected revenue enhances platform profits, as the increase in transaction commissions is the greatest.

With regard to the platform's pricing strategies, reducing CPA while 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. This strategy also lowers the likelihood advertisers will list items to gain clicks (possibly in the hope of own-site future sales) while hoping not to sell them on the platform. The platform can further enhance its revenue in equilibrium by auctioning the top 5 positions (i.e., limiting the adverting slots) based on CPC pricing, then ordering by expected revenue from position 6 and lower.. Limiting the advertising slots extracts the rents from the advertisers with the highest valuations, and ordering items by expected revenue for slots 6 and below generates greater returns from sales - thus helping revenue on both sides of the platform.

While this paper investigates a broad range of interactions among buyers, sellers, and the platform in an online marketplace platform, a number of additional extensions are possible. First, on the buyer side, one can extend our model to incorporate the consumer's site visit incidence decision that can depend on which sellers advertise and how the platform ranks advertised versus organic products. Another possible extension is to consider cross-category and cross-store browsing, clicking, and purchase, which will yield some novel insights on platform strategies. In addition, it is possible that consumers consider even the non-clicked items and the latent consideration set is worth exploring. Future research is also warranted regarding which information should be presented to consumers on the product listing page versus the product detail page.[46]

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 two-sided online marketplaces represent an important direction for future analysis. With multi-homing consumers, cross-promotion and advertising can

[46] Changes in the set of attributes presented on the product listing page versus the product detail page may affect browsing and clicking costs. With further variation in data (e.g. exogeneous variation in which content is present on the product listing page versus the product detail page), the consumer model could be extended to incorporate these potential changes in costs.

produce potential benefits.

Third, our search model can be applied to blogs and social media websites where visitors search a list of article titlesin a top-to-bottom sequence and decide which ones to click on and 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 products to gather further information. 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.

References

Aggarwal, G., J. Feldman, S. Muthukrishnan, and M. Pál. 2008. "Sponsored search auctions with markovian users." In *International Workshop on Internet and Network Economics,* 621–628. Springer.

Ansari, A., and C. F. Mela. 2003. "E-customization." *Journal of Marketing Research:* 131–145.

Arcidiacono, P., and R. A. Miller. 2011. "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity." *Econometrica* 79 (6): 1823–1867.

Athey, S., and G. Ellison. 2011. "Position Auctions with Consumer Search." *The Quarterly Journal of Economics:* qjr028.

Balseiro, S. R., O. Besbes, and G. Y. Weintraub. 2015. "Repeated auctions with budgets in ad exchanges: Approximations and design." *Management Science* 61 (4): 864–884.

Blake, T., C. Nosko, and S. Tadelis. 2015. "Consumer Heterogeneity and Paid Search Effectiveness: A Large-Scale Field Experiment." *Econometrica* 83 (1): 155–174.

Bronnenberg, B. J., B. J. Kim, and C. F. Mela. 2016. "Zooming In on Choice: How Do Consumers Search for Cameras Online?" *Marketing Science.*

Chan, T. Y., and Y.-H. Park. 2015. "Consumer Search Activities and the Value of Ad Positions in Sponsored Search Advertising." *Marketing Science.*

Chen, Y., and C. He. 2011. "Paid placement: Advertising and search on the internet*." *The Economic Journal* 121 (556): F309–F328.

Chen, Y., and S. Yao. 2014. "Search with Refinement." *Available at SSRN 2130646.*

De los Santos, B., A. Hortacsu, and M. R. Wildenbeest. 2012. "Testing models of consumer search using data on web browsing and purchasing behavior." *The American Economic Review* 102 (6): 2955–2980.

De los Santos, B., A. Hortacsu, and M. R. Wildenbeest. 2013. "Search with Learning."

Edelman, B., M. Ostrovsky, and M. Schwarz. 2007. "Internet advertising and the generalized second-price auction: Selling billions of dollars worth of keywords." *American economic review* 97 (1): 242–259.

Granka, L. A., T. Joachims, and G. Gay. 2004. "Eye-tracking analysis of user behavior in WWW search." In *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval,* 478–479. ACM.

Guadagni, P. M., and J. D. Little. 1983. "A logit model of brand choice calibrated on scanner data." *Marketing science* 2 (3): 203–238.

Gupta, S. 1988. "Impact of sales promotions on when, what, and how much to buy." *Journal of Marketing research:* 342–355.

Honka, E. 2013. "Quantifying search and switching costs in the US auto insurance industry." *Available at SSRN 2023446.*

Honka, E., A. Hortaçsu, and M. A. Vitorino. 2017. "Advertising, consumer awareness, and choice: Evidence from the us banking industry." *The RAND Journal of Economics* 48 (3): 611–646.

Iyer, K., R. Johari, and M. Sundararajan. 2014. "Mean field equilibria of dynamic auctions with learning." *Management Science* 60 (12): 2949–2970.

Jeziorski, P., and S. Moorthy. 2017. "Advertiser prominence effects in search advertising." *Management Science.*

Jeziorski, P., and I. Segal. 2015. "What makes them click: Empirical analysis of consumer demand for search advertising." *American Economic Journal: Microeconomics* 7 (3): 24–53.

Kamakura, W. A., and G. Russell. 1989. "A probabilistic choice model for market segmentation and elasticity structure." *Journal of marketing research* 26:379–390.

Kempe, D., and M. Mahdian. 2008. "A cascade model for externalities in sponsored search." In *International Workshop on Internet and Network Economics,* 585–596. Springer.

Kim, J. B., P. Albuquerque, and B. J. Bronnenberg. 2010. "Online demand under limited consumer search." *Marketing science* 29 (6): 1001–1023.

Kim, J. B., P. Albuquerque, and B. J. Bronnenberg. 2015. "The probit choice model under sequential search with an application to online retailing."

Koulayev, S. 2013. "Estimating demand in online search markets, with application to hotel bookings." *Federal Reserve Bank of Boston Working Paper,* nos. 09-16.

Krishna, V. 2009. *Auction theory.* Academic press.

Krusell, P., and A. A. Smith Jr. 1998. "Income and wealth heterogeneity in the macroeconomy." *Journal of Political Economy* 106 (5): 867–896.

Lee, D., and K. I. Wolpin. 2006. "Intersectoral labor mobility and the growth of the service sector." *Econometrica* 74 (1): 1–46.

Lu, S., and S. Yang. 2016. "A Two-Sided Market Analysis of Behaviorally Targeted Display Advertising." *Job Market Paper.*

Mojir, N., and K. Sudhir. 2016. "Price Search Across Stores and Across Time."

Rust, J. 1987. "Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher." *Econometrica: Journal of the Econometric Society:* 999–1033.

Sahni, N. S., and H. Nair. 2016. "Native advertising, sponsorship disclosure and consumer deception: Evidence from mobile search-ad experiments." Working paper.

Seiler, S. 2013. "The impact of search costs on consumer behavior: A dynamic approach." *Quantitative Marketing and Economics* 11 (2): 155–203.

Simonov, A., C. Nosko, and J. M. Rao. 2015. "Competition and Crowd-Out for Brand Keywords in Sponsored Search."

Ursu, R. M. 2015. "The Power of Rankings: Quantifying the Effects of Rankings on Online Consumer Search and Choice." *Job Market Paper.*

Weintraub, G. Y., C. L. Benkard, and B. Van Roy. 2005. "Oblivious equilibrium: A mean field approximation for large-scale dynamic games." In *NIPS.*

Yao, S., and C. F. Mela. 2011. "A dynamic model of sponsored search advertising." *Marketing Science* 30 (3): 447–468.

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 10 presents the shares by (sub) categories. The main landing page category constitutes the largest share of visits and impressions and the second largest share of clicks and purchases.

Table 10: Shares of Visits, Browses, Clicks and Purchases

Top Categories	% Visits	% Impressions	% Clicks	% 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

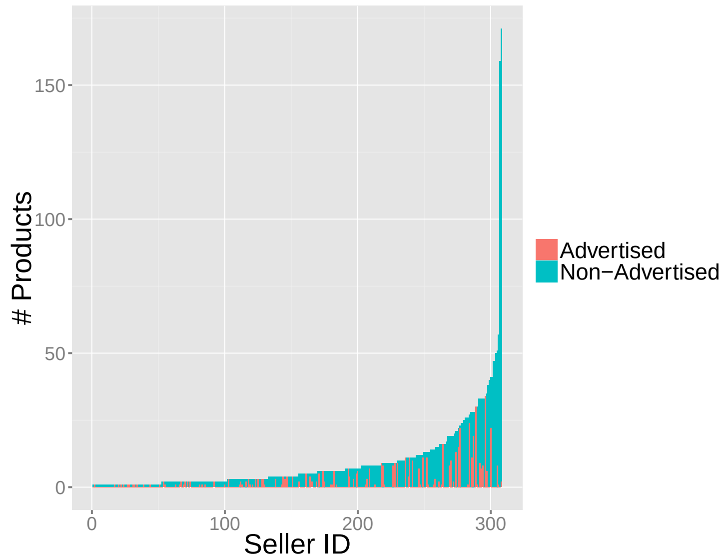
A.2.1 Product Listing and Advertising Decisions

Figure 9 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 11 documents some observable aspects that suggest different valuations across products via a logit regression analysis of the products' advertising status against independent variables,

Figure 9: 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, and stone products are advertised more frequently. Last, 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 9). Brand Group 1 is 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 Group 0. While

Table 11: 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

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 12). We find no significant relationship, suggesting the plausibility of the exogenous pricing assumption we employ.

Table 12: 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 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 its own website, but incur fees in various amounts if it is sold elsewhere. Accordingly, in Table 13, 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 13: 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, the 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

$$h\left(\mathbf{Z}_{j(1)}, \mathbf{X}_{j(1)}, ..., \mathbf{Z}_{j(T^r)}, \mathbf{X}_{j(T)}\right) = h_1(\mathbf{X}_{j(1)} \mid \mathbf{Z}_{j(1)}) h_2(\mathbf{Z}_{j(1)}) \prod_{t=2}^{T} h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)}) h_2(\mathbf{Z}_{j(t)} \mid \mathbf{Z}_{j(t-1)}) \tag{19}$$

Belief State Transitions The belief state transitions can be expressed as

$$\begin{aligned} f_1^s\left(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}\right) &= h_2(\mathbf{Z}_{j(t+1)} \mid \mathbf{Z}_{j(t)}) \\ f_0^c\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) &= \mathbf{1}\left(u_{it}^* = u_{it-1}^*\right) \\ f_1^c\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) &= f^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) \end{aligned} \tag{20}$$

The first line indicates consumer's belief on transition of $\mathbf{Z}_{j(t+1)}$ when browsing continues, and the actual empirical distribution h_2 is used for this rational belief. The second line represents the belief state transition when the consumer does not click. In this case, the maximal utility in hand remains the same, because the consumer simply moves on to browse the next item. The third line expresses the belief state transition when a consumer does click on product $j(t)$, in which case the maximal utility u_{it}^* is believed to transit with distribution $f^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right)$. That is, there is some likelihood of drawing an item better than those clicked before.

Using the iid $N(0, \sigma_\epsilon^2)$ assumption made on ϵ_{ij} and the additive separability of utility specification, $f^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right)$ can further be decomposed into

$$f^u\left(u_{it}^* \mid u_{it-1}^*, \mathbf{Z}_{j(t)}\right) = \begin{cases} \int_{\mathbf{X}_{j(t)}} \Phi\left(\frac{u_{it}^* - \mathbf{X}_{j(t)}\alpha - \mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)}) & \text{when } u_{it}^* = u_{it-1}^* \\ \int_{\mathbf{X}_{j(t)}} \frac{1}{\sigma_\epsilon}\phi\left(\frac{u_{it}^* - \mathbf{X}_{j(t)}\alpha - \mathbf{Z}_{j(t)}\beta}{\sigma_\epsilon}\right) h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)}) & \text{when } u_{it}^* > u_{it-1}^* \end{cases} \tag{21}$$

where ϕ and Φ are pdf and cdf of standard normal distribution, respectively. The first line indicates the probability that the clicked product yields a lower utility than u_{it}^*, the maximal utility in the consideration set formed prior to the click. The second line presents the probability of a click yielding a better product than previously discovered, u_{it-1}^*. The distribution for u_{it}^* (maximal utility in the consideration set at step t of search) is truncated from below by definition, with the truncation point given by u_{it-1}^*. As the u_{it-1}^* a consumer has in his hand weakly increases with the number of items previously clicked, the expected benefit of clicking also decreases in the number of items clicked, all others equal (e.g., the observed attributes).[47] Finally, $h_1(\mathbf{X}_{j(t)} \mid \mathbf{Z}_{j(t)})$ represents product attribute state transition

[47]For example, if a consumer clicks and draws high ϵ_{ij}s in the beginning of the search process, this consumer

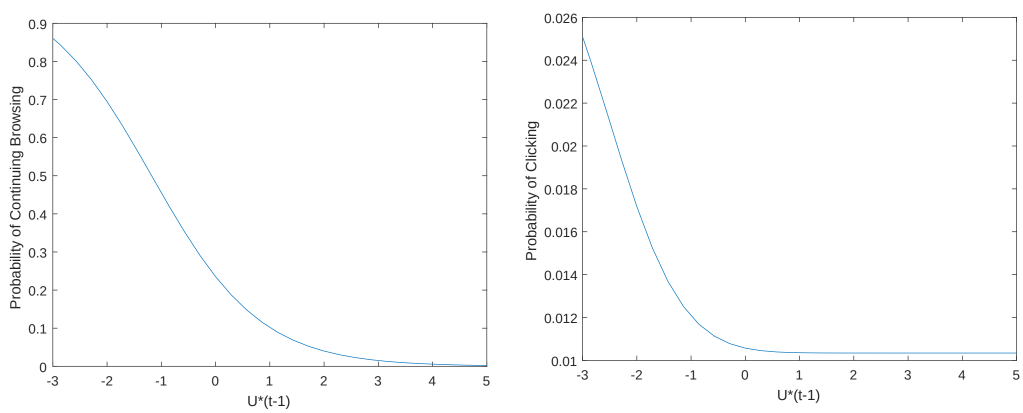
as defined in Equation (19).

B.2 Additional Discussion on Sequential Search Process

B.2.1 Existence and Uniqueness of the Consumer Model Solution

In our search model, a consumer is presented with an *exogenous* search sequence, and the optimal stopping problem closely resembles Rust's replacement model (Rust 1987, Seiler 2013). As the maximum utility of the items in the consideration set, u^*_{t-1}, increases, the expected incremental increase in u^*_t from an additional browsing (or clicking) event decreases, which in turn decreases the probability of continuing browsing (or clicking an item) with respect to u^*_{t-1}. Eventually, this incremental increase in u^*_t becomes so small relative to a constant clicking costs that search stops. This guarantees the existence and the uniqueness of the solution.[48] In Figure 19, we plot probability of continuing browsing and clicking with respect to u^*_{t-1}, for a given $\mathbf{Z}_{j(t)}$,

Figure 10: Optimality of Search



B.2.2 Possibility of Recall (Non-Terminal Purchase)

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

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.

[48] Additionally, a single choice (purchase) assumption within a visit is required for the uniqueness of the solution. This assumption follows the definition of 'visit' we construct. In our data, about 10% were multiple purchases (= 2 purchases) within the same search session. In such cases, we assume that a new visit (search session) starts after purchasing the first item.

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).

With the introduction of the match value, ε_t, separately from the structural error term for click, $\eta^c_{d^c it}$, we allow consumers to purchase the non-terminal clicked item, even with a constant marginal browsing/clicking cost per alternative. 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 browsed or clicked. This is not possible in Weitzman's search model but is common in our data. In this regard, we provide an additional modeling 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 Browsing, Clicking, and Purchase

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

Clicking Decision Likelihood at Position t The likelihood of observing click decision d^c_{it}, conditional on browsing and the (observed and unobserved) states can be defined as

$$\begin{aligned}&\mathcal{L}^{click|browse}_t(d^c_{it} \mid u^*_{it-1}, \mathbf{Z}_{j(t)}; \Theta_1)\\ &= \left[p^c_0\left(u^*_{it-1}, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d^c_{it}=0)} \times \left[1 - p^c_0\left(u^*_{it-1}, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d^c_{it}=1)} \end{aligned} \tag{22}$$

where $p^c_0\left(u^*_{it-1}, \mathbf{Z}_{j(t)}; \Theta_1\right)$ is defined in equation (4).

Browsing Decision Likelihood at Position t The likelihood of observing browsing decision d^s_{it}, based on the (observed and unobserved) states can similarly be defined as

$$\begin{aligned}&\mathcal{L}^{browse}_t(d^s_{it} \mid u^*_{it}, \mathbf{Z}_{j(t)}; \Theta_1)\\ &= \left[p^s_0\left(u^*_{it}, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d^s_{it}=0)} \times \left[1 - p^s_0\left(u^*_{it}, \mathbf{Z}_{j(t)}; \Theta_1\right)\right]^{\mathbf{1}(d^s_{it}=1)} \end{aligned} \tag{23}$$

where $p^s_0\left(u^*_{it}, \mathbf{Z}_{j(t)}; \Theta_1\right)$ is given by equation (8).

Consumer Purchase Decision Likelihood at Position t Let T^s_i reference the position where individual i chooses to stop browsing such that $d^s_{iT^s_i} = 0$. Also denote T^p_i as the position in the browsing sequence where the purchased product is presented to the consumer, such that $d^p_{ij(T^p_i)} = 1$ (If the consumer chooses the outside option of not purchasing, then $d^p_{ij(T^p_i=0)} = 1$). The final consideration set $\Gamma_i = \Gamma_{iT^S_i}$ contains $K_{iT^S_i}$ number of products, and we index them as $\{1, ..., p^*, ...K_{iT^S_i}\}$ in the order encountered for consideration. Further we define $t(p)$ as the browsing 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 $\{1, ..., (p^* - 1)\}$; second, 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 clicked items not chosen prior to the chosen alternative differ from those clicked items encountered after the chosen alternative. More specifically, we know that all items clicked 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 click. However, for items not chosen prior to the chosen alternative, u^* can increase with each item clicked, even though u^* will not be higher than the chosen alternative. Therefore, when determining how choice affects the likelihood, we need to explicitly condition on the order in which the clicked 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 clicked prior to the chosen 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[49]

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

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 among the ones clicked 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 clicked after the chosen item** : when $T_i^p < t(p) \leq T_i^s$

   If a product is clicked 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

[49] 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}^*.

unobserved u^*_{it}, can be written as

$$\begin{aligned}&\mathcal{L}_t^{purchase|click,browse}\left(u^*_{it} \mid u^*_{it-1}, \mathbf{Z}_{j(t)}, \mathbf{X}_{j(t)}\right)\\&= \left[\mathbf{1}\left(t \leq T_i^p - 1\right) f_1^u(\cdot) + \mathbf{1}\left(t = T_i^p\right) f_2^u(\cdot) + \mathbf{1}\left(T_i^p < t \leq T_i^s\right) f_3^u(\cdot)\right]^{1\left(d^c_{it}=1\right)}\\&\times \left[\mathbf{1}\left(u^*_{it} = u^*_{it-1}\right)\right]^{1\left(d^c_{it}=0\right)} \qquad (24)\end{aligned}$$

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

Combining Browsing, Clicking, and Choice We define the total likelihood of observing the whole path of choices $\mathbf{d}_i = \{d^c_{i1}, ..., d^c_{iT_i^s}, d^s_{i1}, ..., d^s_{iT_i^s}, d^p_{i1}, ..., d^p_{iT_i^s}\}$ based on the (observed and unobserved) states as

$$\begin{aligned}&\mathcal{L}(\mathbf{d}_i \mid u^*_{i0}, ..., u^*_{iT_i^s}, \mathbf{Z}, \mathbf{X}; \Theta_1)\\&= \prod_{t=1}^{T_i^s} \mathcal{L}_t^{browse} \mathcal{L}_t^{click|browse} \mathcal{L}_t^{purchase|click,browse}\end{aligned}$$

where $\mathcal{L}_t^{browse}$, $\mathcal{L}_t^{click|browse}$, and $\mathcal{L}_t^{purchase|click,browse}$ are defined in equations (23), (22), and (24) respectively. This total likelihood is derived from multiplying over the likelihood of clicking and browsing decisions at $t = 1, ..., T_i^s$, and the transition of unobserved u^* is represented within $\mathcal{L}_t^{purchase|click,browse}$.

Integrating Out Unobservable States Now we define the likelihood of observing $\mathbf{d}_i = \{d^c_{i1}, ..., d^c_{iT_i^s}, d^s_{i1}, ..., d^s_{iT_i^s}, d^p_{i1}, ..., d^p_{iT_i^s}\}$ 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 $u^*_{it}|u^*_{it-1}$ is governed by $\mathcal{L}_t^{purchase|click,browse}$ as discussed above. This likelihood ensures that the purchased product has the highest utility among all clicked 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 browse quite extensively, yet the browsing 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 browsing 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:[50]

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, $Emax^{browse,\,k}$.

    (a) Given $Emax^{browse,\,k}$, compute the conditional value function for the click decision based on equation (2). Then these conditional value functions are used to compute the conditional choice probability of no click, p_t^c, as defined in equation (4) and also the expected future value of click, $Emax^{click,\,k}$, as defined in equation (7).

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

[50]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, and 50 grid spaces respectively. The end points of u^* range were also extended to $[-5,\ 10]$. In all cases, the estimates were stable.

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 (15), 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 14. σ_ϵ is normalized to be one for identification purposes, and constant functional forms were used for clicking and browsing costs. The recovered parameters are all close to the true values with small standard errors.

Table 14: 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	clicking cost	0.4	**0.3983** (0.0312)	**0.4029** (0.0342)
γ_2	browsing cost	0.3	**0.3082** (0.0093)	**0.3108** (0.0149)

The last column shows the results when purchase data are ignored, and only browsing and clicking observations are used in estimation. Although clicking and browsing 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 clicks 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 clicked, 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 Model Fit

Table 15 presents the in-sample and out-of-sample model fit of the consumer model. For the in-sample, 1000 set of 956 visits is simulated and the key statistics are compared to those of the data. The heterogeneity on the cost parameters significantly improves the fit of the distribution (e.g., SD). For the out-of-sample, we hold out randomly selected 190 visits (about 20% of the sample) and then estimate the model using only 766 visits. Based on the new estimates, we simulate 1000 set of 956 visits to calculate the key statistics. Overall the model fits well.

Table 15: The Consumer Model Fit

# Per Visit		Median	Mean	SD
Browsing Length	Data	20	77.8	277.0
(Impressions)	1 Segment (In)	54.0 (2.49)	77.8 (2.43)	77.6 (3.58)
	4 Segments (In)	26.3 (1.28)	78.2 (7.13)	215.8 (28.8)
	4 Segments (Out)	27.1 (1.32)	90.7 (9.22)	283.9 (42.0)
Clicks	Data	0	0.8	3.0
	1 Segment (In)	0.00 (0.06)	0.83 (0.04)	1.23 (0.06)
	4 Segments (In)	0 (0)	0.83 (0.09)	2.61 (0.37)
	4 Segments (Out)	0 (0)	0.69 (0.07)	2.31 (0.33)
Purchase (Demand)	Data	0	0.04	0.2
	1 Segment (In)	0 (0)	0.05 (0.01)	0.21 (0.01)
	4 Segments (In)	0 (0)	0.04 (0.01)	0.20 (0.02)
	4 Segments (Out)	0 (0)	0.04 (0.01)	0.19 (0.01)
#clicks	Data	0	1.14	2.9
/#browses (%)	1 Segment (In)	0.00 (0.02)	1.07 (0.08)	2.34 (0.70)
	4 Segments (In)	0 (0)	1.15 (0.12)	3.54 (0.81)
	4 Segments (Out)	0 (0)	0.92 (0.11)	3.21 (0.84)
#purchases	Data	0	7.4	22.2
/#clicks (%)	1 Segment (In)	0 (0)	5.87 (0.98)	20.1 (1.94)
	4 Segments (In)	0 (0)	7.06 (1.37)	21.2 (2.59)
	4 Segments (Out)	0 (0)	7.13 (1.48)	21.6 (2.79)

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:

$$\begin{aligned} Rank_{j,t,d_j^a,\mathbf{d}_{-j}^a} &= Rank\,(\text{Own Score}_{jt},\ \text{Others' Scores}_{-jt}) \\ &= Rank\,\big(\text{Popularity}_{jt},\ \text{Slot Adjust}_{jt}, \text{Days Listed}_{jt}, \text{Advertising}_{jt}, \text{Others' Scores}_t\big) \end{aligned} \tag{25}$$

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 × 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 the rank function yields

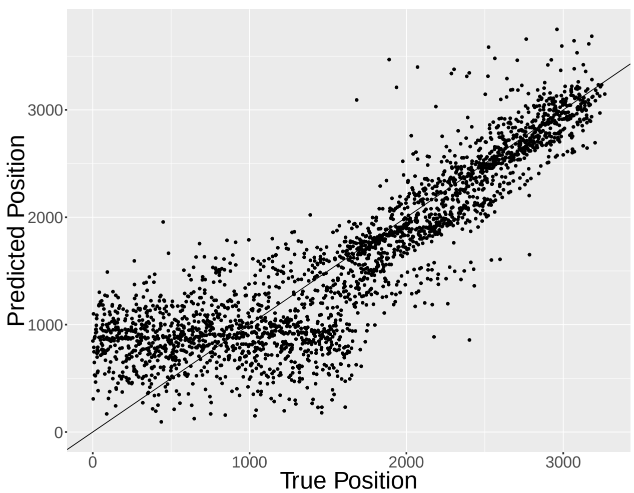
$$\begin{aligned} Rank_{j,t,d_j^a,\mathbf{d}_{-j}^a} = Rank\,(&\text{Popularity}(\text{Rank}_{jt},\ \text{Days Listed}_{jt},\ \text{Unobserved}_j), \\ &\text{Slot Adjust}(Rank_{jt}, DaysListed_{jt}), \\ &\text{Days Listed}_{jt},\ \text{Advertising}_{jt},\ Others'Scores_t\big) \\ Rank_{j,t,d_j^a,\mathbf{d}_{-j}^a} = Rank\,\big(&\text{Unobserved}_j,\ \text{Days Listed},\ \text{Advertising}_{jt},\ \text{Others' Scores}_t\big) \end{aligned}$$

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 a 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. Last, 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

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

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 plots product position based on the platform's algorithm on the x-axis, and the sellers' beliefs about product placements on the y-axis on a given day. Although the sellers' beliefs are based on only aggregate and individual states, sellers' approximated beliefs hew closely to rational expectations.

Figure 11: Beliefs on Product Placement



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 (16).

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 Stage 1. For estimation, we compute $\left(E_t(\mathbf{d}_{-j}^a),\ J_t\right)$ under the observed advertising strategies and use these two statistics as the aggregate beliefs.

2. Compute consumer responses based on product placement beliefs $\left(\widehat{Rank_{j,t,d_j^a=0,\mathbf{d}_{-j}^a}},\ \widehat{Rank_{j,t,d_j^a=1,\mathbf{d}_{-j}^a}}\right)$

Using the consumer demand model, simulate consumer demand, click, and impressions $\left(\widehat{D_{j,t,,d_j^a,\mathbf{d^a_{-j}}}},\ \widehat{C_{j,t,d_j^a,\mathbf{d^a_{-j}}}},\ \widehat{I_{j,t,d_j^a,\mathbf{d^a_{-j}}}}\right)$ by displaying product j at position $\left(\widehat{Rank_{j,t,d_j^a,\mathbf{d}^a_{-j}}}\right)$. This is done at the daily level, and these simulated responses are aggregated across time periods to form product j's lifetime demand, clicks, and impressions, which are entered into equations (11) and (12).[51]

3. Accounting for uncertainty in $\left(\widehat{Rank_{j,t,d_j^a=0,\mathbf{d}^a_{-j}}},\ \widehat{Rank_{j,t,d_j^a=1,\mathbf{d}^a_{-j}}}\right)$

   The seller faces uncertainty regarding $\left(E_t(\mathbf{d}^a_{-j,}),\ J_t\right)$, and therefore ultimately $\left(\widehat{Rank_{j,t,d_j^a=0,\mathbf{d}^a_{-j}}},\ \widehat{Rank_{j,\ldots}}\right.$ This uncertainty arises because sellers do not know ξ_j, but instead only know its distribution. To account for the uncertainty in the sellers' beliefs regarding rank, we simulate 1000 sets of ξ_j, generating 1000 sets of $\left(E_t(\mathbf{d}^a_{-j,}),\ J_t\right)$, leading to 1000 sets of $\left(\widehat{Rank_{j,t,d_j^a=0,\mathbf{d}^a_{-j}}},\ \widehat{Rank_{j,t,d_j^a=1,\mathbf{d}^a_{-j}}}\right)$, and then ultimately 1000 sets of $\left(\widehat{D_{j,t,,d_j^a,\mathbf{d^a_{-j}}}},\ \widehat{C_{j,t,d_j^a,\mathbf{d^a_{-j}}}},\ \widehat{I_{j,t,d_j^a,\mathbf{d^a_{-j}}}}\right)$. We compute the expected value of $\left(\widehat{D_{j,t,,d_j^a,\mathbf{d^a_{-j}}}},\ \widehat{C_{j,t,d_j^a,\mathbf{d^a_{-j}}}},\ \widehat{I_{j,t,d_j^a,\mathbf{d^a_{-j}}}}\right)$ to account for the uncertainty in sellers' beliefs.

Stage 3 - Estimate Seller Model Parameters

1. Starting with the iteration step $iter = 0$, initialize the advertiser model parameters $\Theta_2^{iter} \equiv \left(\theta^{iter},\ \theta^{D,iter},\ \theta^{C,iter},\ \theta^{I,iter},\ \delta\right)$.

2. Using equation (13), compute the advertising probability for product j based on the aggregated consumer responses obtained in Stage 2, when advertising $\left(\widehat{D_{j,d_j^a=1,\mathbf{d}^a_{-j}}},\ \widehat{C_{j,d_j^a=1,\mathbf{d}^a_{-j}}},\ \widehat{I_{j,d_j^a=1,\mathbf{d}^a_{-j}}}\right)$ and not advertising $\left(\widehat{D_{j,d_j^a=0,\mathbf{d}^a_{-j}}},\ \widehat{C_{j,d_j^a=0,\mathbf{d}^a_{-j}}},\ \widehat{I_{j,d_j^a=0,\mathbf{d}^a_{-j}}}\right)$ and the given set of parameters Θ_2^{iter}.

3. Compute the log-likelihood in equation (17), based on the advertising probabilities computed. Optimize the log-likelihood to compute the new set of parameters Θ_2^{iter+1}.

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

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

decisions until convergence. This convergence will ensure that the aggregate beliefs are consistent with the underlying advertisers' decisions in equilibrium.[52] 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 (16)) used in 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 (16) 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 (20) and (21) based on $\mathbf{d}^{a,k}$ and the platform's actual ranking algorithm.

4. Next step is to estimate the effect of advertising on product placement and consumer responses (impressions, clicks and purchases). To compute this, we run Steps 1 - 3 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. Changing the fee structure can affect the sellers' listing behavior (for example, a seller would delist an item if the expected listing fees are higher than the expected gains from listing). To account for the change in the seller's listing behavior, we impose a participation constraint that each seller's utility is greater than the minimum of the seller utilities estimated in the actual fee structure setting.

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.

[52] 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.

D Full Sample Results

In the analysis reported in the paper, we restrict our attention to the users with at least one purchase (within the estimation period, across all categories) in our analyses. Arguably, those that do not make purchases generate advertiser value via impressions and clicks. To obtain a better sense of the magnitude of potential bias arising from the sample selection, we re-estimate our demand side model with the 'full sample' of consumers (including both with and without purchase), and use these new estimates to infer advertiser valuations. In the full sample, we observe $72,030$ individuals meeting our criteria, with a total of $85,632$ visits. An individual makes 1.2 visits in average (median 1) during the sample period. These consumers browse $2,256,244$ products in total, among which $24,870$ are considered and 40 are purchased within the main page product feed.

D.1 The Consumer Model

Except for the constant, the preference parameters for the full sample are within 2 standard deviations (do not appear to significantly differ) from the purchase sample estimates. The lower constant reflects the data pattern, where the mean purchase rate for the full sample is lower than that of the purchase sample. The average marginal costs of browsing and clicking are \$0.94 and \$3.92, respectively, which are higher than those estimated using the purchase sample. Higher browsing/clicking costs are also consistent with the data pattern; the consumers in the full sample are less likely to browse and click within a visit, as they are less interested in purchasing the products.

D.2 The Advertiser Model

The estimates for the advertiser model predicated upon the full sample results (i.e., full sample demand estimates and simulations of full sample consumer behaviors) are reported in the second column in Table 17.

All estimates are similar, except for the marginal valuation for purchase, click, and impression. This difference in estimates for marginal value arises because the total number of expected purchases, clicks, and impressions for a given product are larger for the full sample, leading to decreased mean values *per* each purchase, click, and impression. Although the per click (or impression) value is smaller, we find that the *total* advertiser valuations from purchases, clicks, and impressions using the full sample are indeed similar to the total valuations from the purchase sample.

As total advertiser valuation is largely unchanged, the advertisers' total willingness to pay to the platform (= smaller willingness to pay per click $\times$ larger total number of clicks in

Table 16: The Consumer Model Estimates

	Sample	Purchase	Full
Preference			
Type1	# Pictures (X)	$\mathbf{0.18}$ (0.07)	$\mathbf{0.11}$ (0.06)
	Log (Price) (Z)	$\mathbf{-0.29}$ (0.10)	$\mathbf{-0.27}$ (0.08)
	# Likes (Z)	-0.00 (0.01)	-0.01 (0.00)
	Constant	$\mathbf{-2.67}$ (0.09)	$\mathbf{-4.39}$ (0.30)
Cost			
Type1	Clicking	$\mathbf{1.42}$ (0.02)	$\mathbf{1.66}$ (0.00)
	Browsing	$\mathbf{0.16}$ (0.00)	$\mathbf{0.20}$ (0.00)
Type2	Clicking	$\mathbf{1.77}$ (0.03)	$\mathbf{1.73}$ (0.01)
	Browsing	$\mathbf{0.15}$ (0.00)	$\mathbf{0.15}$ (0.00)
Type3	Clicking	$\mathbf{1.16}$ (0.04)	$\mathbf{1.29}$ (0.01)
	Browsing	$\mathbf{0.20}$ (0.00)	$\mathbf{0.17}$ (0.00)
Type4	Clicking	$\mathbf{1.76}$ (0.05)	$\mathbf{0.87}$ (0.01)
	Browsing	$\mathbf{0.17}$ (0.00)	$\mathbf{0.25}$ (0.00)
Type Probability			
	Pr(Type1)	$\mathbf{0.05}$ (0.01)	$\mathbf{0.87}$ (0.01)
	Pr(Type2)	$\mathbf{0.04}$ (0.01)	$\mathbf{0.06}$ (0.00)
	Pr(Type3)	$\mathbf{0.20}$ (0.04)	$\mathbf{0.03}$ (0.00)
N		$74,400$	$2,256,244$
LL		$-9,077$	$-477,604$
BIC		$18,344$	$955,457$

the full sample) will also be largely similar. Thus, the key counterfactual findings based on the advertiser model (e.g., percentage change in total seller welfare and platform profits from the baseline) yield essentially the same insights regardless of whether one uses the purchase sample or the full sample.

The cautionary lesson from using the purchase sample to impute advertiser valuations lies in interpreting ‘marginal valuation’ and ‘marginal fee’. The marginal valuations estimated using the purchase sample are the marginal valuations per purchase, click, and impression of those with at least one purchase. Moreover, the changes in marginal fees (f^A, f^T, f^C, f^I) under the counterfactual exercises should be interpreted as the marginal fee charged to those with at least one purchase history. However, more material for the insights gained from the policy simulations (e.g., the percentage change in platform's profits when adopting CPC auction on clicks) rely largely on the total valuation.

Table 17: The Advertiser Model Estimates

	Sample	Purchase	Full
θ^D	Demand	0.52 (0.410)	0.01 (0.007)
θ^C	log(Clicks+1)	**0.006** (0.001)	0.000 (0.000)
θ^I_1	log(Impressions (in thousand))	0.000 (0.000)	0.000 (0.000)
δ	Marginal Cost Mean	**0.76** (0.078)	**0.74** (0.03)
σ_δ	Marginal Cost SD	**0.007** (0.001)	**0.008** (0.001)
θ	Constant	$-$**0.98** (0.056)	$-$**0.96** (0.056)
	Brand Group 1 (# product listing > 150)	$-$**1.66** (0.160)	$-$**1.63** (0.157)
	Brand Group 2 ($85 <$# product listing≤ 150)	$-$**0.38** (0.060)	$-$**0.33** (0.060)
	Include URL	**0.27** (0.063)	**0.21** (0.086)
	Silver	**0.43** (0.153)	**0.43** (0.157)
	Stone	**0.19** (0.087)	**0.30** (0.068)
	Bracelet	**0.28** (0.068)	**0.29** (0.063)
	Refundable	**0.26** (0.059)	**0.26** (0.058)
	LL ($N = 2853$)	-1263.7	-1284.3