

Platform Search Design and Market Power*

H. Tai Lam[†]

University of California, Los Angeles

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Abstract

On the Amazon.com marketplace, both Amazon and small businesses compete in offering retail products. However, Amazon chooses what products consumers see when they search. Products sold by Amazon may have a better position compared to small business products, but the effects on consumers and sellers are unclear. Policymakers have expressed antitrust concerns about this, suspecting “self-preferencing” and “gatekeeper” market power. To study this, I develop a model where heterogeneous consumers search for differentiated products arranged on an acyclic graph (i.e., tree). Firms price in response to consumer search and how their products are arranged—highlighting how search design determines market structure. The model endogenizes consideration set formation and recovers the correlated distribution of consumer preferences and search costs. Estimated on Amazon data, I show that not accounting for product arrangement (e.g., search results and BuyBox) leads to incorrect price elasticity estimates. I provide three results on market power and antitrust policies using counterfactual product arrangements. (i) To isolate the effect of Amazon’s position advantage, I remove it through a “neutral” product arrangement. Profits shift from Amazon to small businesses, confirming Amazon’s sizable market power. However, consumers reduce their search intensity in response to reduced option value and welfare decreases. This suggests Amazon’s incentives and consumers’ preferences are aligned, weakening the claim of self-preferencing. (ii) Banning the platform owner from also being a seller reduces consumer welfare; prices increase even though product variety is unaffected. (iii) I propose an alternate policy, splitting the platform into an Amazon side and a small-business side. Giving consumers the ability to search for and “support small businesses” would alleviate the market power imbalance without harming consumers.

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[†]Email: tai.lam@u.northwestern.edu

1 Introduction

Online retail platforms are the marketplace for billions of products. These products may be offered by the platform owner or the millions of small businesses (Third-Party Sellers; TPSs) that operate on the platform. However, consumers using these platforms will not see *all* relevant products before making their purchase decision. Rather, the platform selects the subset of products that consumers see when they search. This directly influences the number and type of consumers that TPSs and the platform owner compete for. Furthermore, the arrangement of the products shown is important. The platform owner can influence the consumer search process by placing some products within easy reach. Conversely, hard to reach products are only seen by consumers with low enough search costs or strong enough preferences to make search worthwhile. How sellers (both the platform owner and TPSs) price their products is also affected—there are fewer competitors among the easy to reach products and the extent of competition depends on the proximity of substitutable products.

Platform owners exert market power on TPSs by choosing the product arrangement and influencing consumer search behavior. Here, market power refers to the platform owner’s ability to place its products in advantageous positions. Policymakers are naturally concerned about this market power affecting TPSs and consumers. As the US Congressional Subcommittee on Online Platforms and Market Power put it, “a handful of gatekeepers have come to capture control over key arteries of online commerce.”¹

Two natural questions come from the platform’s role as a “gatekeeper”—one positive and one normative. (i) How does the platform’s product arrangement affect consumer welfare and firm profits? For example, what share of the platform owner’s profits comes from placing its products in better positions (e.g., at the top of the search results) and how does this reduce small businesses (TPSs) profits? For consumers, are valuable products being kept out of reach? Or does the arrangement reflect a difference in value between TPS and platform owner products? (ii) Normatively, what would be the effect of the antitrust policies proposed by policymakers to address the market power imbalance between the platform owner and TPSs? This includes the vertical operation ban where the platform owner is prevented from also operating as a seller. Are there alternate policies that could better address this imbalance?

To answer these questions, we need a tractable model to understand how consumers will change both their search and purchase behavior in response to alternate product arrangements. I build such a model where heterogeneous consumers optimally search over products arranged on an acyclic

¹“Antitrust Investigation of the Rise and Use of Market Power Online and the Adequacy of Existing Antitrust Laws and Current Enforcement Levels”, <https://judiciary.house.gov/issues/issue/?IssueID=14921>.

graph (i.e., tree) and firms set prices in response to this search behavior.² I model consumers as having heterogeneous price sensitivity and search costs. They search across both differentiated products (i.e., looking at search results) and homogeneous products (i.e., considering different sellers of the same product) before purchase. Thus, consumers are searching for products in the spectrum of low-quality-and-low-price to high-quality-and-high-price products that best match their preferences. Search decisions are made optimally, this endogenizes the consideration set formation process for commonly-used demand models. Additionally, the model demonstrates that platforms’ “gatekeeper” market power can be understood as the power to decide market structure on the platform and links it to the growing platform search design literature.

I study the Amazon.com retail platform, because it is both the dominant online retailer in the US and the main subject of the ongoing antitrust discussions. I examine products in 58 “Home & Kitchen” categories. The setting can be characterized by: consumers who value variety, dislike price and dislike search to different degrees; a platform owner that sells “core” products (e.g., common brand products like “Hamilton Beach”, in addition to Amazon-branded products like “AmazonBasics”); and small businesses (TPSs) that compete by selling the same common brands, but also a rich set of “fringe” products (e.g., high quality boutique products or very low quality products). TPSs account for around half of all sales on Amazon.com and constitute a significant part of what makes the platform valuable to consumers.

I focus on two important ways in which Amazon’s chosen product arrangement affects consumer search and firm pricing.³ (i) The *search results*, which is the list of differentiated products the platform shows consumers when they enter a search term. This is important for capturing the order in which products will be discovered and what products will not be seen at all (depending on a consumer’s search cost). (ii) The *BuyBox*, which groups sellers selling the same product (i.e., SKU or UPC) together and designates the lowest-price seller as the default.⁴ Thus, Amazon and TPSs often compete on homogeneous products, in addition to competing on differentiated products. While the search results are the main driver of consumer search behavior, the BuyBox is key for capturing the acute pricing pressure the lowest-price seller faces from other sellers selling

²I remain agnostic about the blackbox algorithms that generate the observed arrangement because that objective is not necessary. I recover consumer and firm primitives (i.e., preferences, search costs, product quality and product marginal costs) from observed variation in the product arrangement and prices. Holding fixed these primitives, the model allows calculation of counterfactual outcomes under any observed arrangement. This paper answers questions about how the observed arrangement affect consumers and firms, as opposed to backing out the platforms’ objective in generating the observed arrangement.

³My modeling framework can support more complex forms of product arrangement (e.g., product recommendations in product pages, navigation through categories or use of search filtering tools). However, estimation would require observing information I do not observe with my aggregate data or significantly more variation.

⁴In 98% of instances, the lowest-price seller is also the BuyBox seller (i.e., the default). For the highly demanded and mature “Home & Kitchen” product categories studied, sellers of a homogeneous product are only substantively differentiated by price. For example, 97% of products use Amazon’s shipping services. Other factors that could affect the determination of the default seller (e.g., shipping time or seller rating) exhibit no meaningful variation for that determination.

the same product (i.e., the lowest price might be constrained by how close the second-lowest price is).

I estimate my model using data scraped from Amazon.com, covering the top-selling products in 58 “Home & Kitchen” categories. I provide reduced-form results that demonstrate the importance of the two search design features. Log-log regressions with product fixed effects show that as a product’s position in the search results changes across time, there is a correlated change in demand for the product. I also document how the lowest-price seller is the BuyBox seller in 98% of instances in the mature categories of goods studied here.

I use the structural model to provide counterfactual answers to the two groups of questions posed above. (i) The positive questions of market power and how platform search design affects consumer, Amazon and TPS outcomes. (ii) The normative questions of the effect of antitrust policies suggested by policymakers to address perceived market power imbalance.

For (i), I document that products sold by Amazon are more advantageously positioned than TPS products. However, this is *not* necessarily the “self-preferencing” that policymakers are concerned about. There are many reasons why we may observe such a difference in positions. For example, the search results algorithm may be giving prominence to, and Amazon is simultaneously choosing to sell, more desirable products. To examine the notion of “self-preferencing” and market power, I answer a simpler question—what would be the effect of removing the position advantage Amazon has over TPSs (i.e., equalizing the product arrangement)? In effect, what would happen if Amazon and TPSs competed on an even playing field. This requires a structural model where we can modify the product arrangement, have consumers respond to the new arrangement by *re-optimizing their search* and their purchase, and firms re-optimize their prices in response to their new position within the arrangement. The resulting counterfactual changes in consumer welfare and firm profits reveals how the status quo arrangement generates market power for some firms and reduces it for others.

Specifically, I randomize the position of products in the arrangement, worsening the position of Amazon products and improving the position of TPS products to equalize the two. In this “neutral arrangement” counterfactual, profits shift from Amazon to TPSs, which reflects the market power enjoyed by Amazon under the status quo. In the partial case where firms do not re-optimize prices (i.e. prices are fixed), consumer welfare actually increases—naively suggesting that consumers would in fact have preferred the previously-worse-positioned TPS products over the previously-better-positioned Amazon products. However, once firms re-optimize prices, prices rise due to two effects. First, TPSs with newly advantageous positioning exploit their new market power by increasing prices and second, price competition falls due to less substitutability of the prominent set of products (i.e., there is greater dispersion in expected product characteristics). On the balance,

consumer welfare is actually harmed by this “neutral arrangement”. This reflects the alignment of consumers’ preferences and Amazon’s incentives, and weakens the case for “self-preferential” behavior.

For (ii), I posit antitrust remedies suggested by policymakers to the model, the most prominent of which prevents Amazon from being both the platform owner and a platform participant. TPS profits increase as TPSs replace Amazon in the BuyBox after Amazon exits, such that product variety is largely maintained. However, prices rise sufficiently that consumer welfare is sizeably harmed. I therefore consider a “middle of the road” policy—splitting the platform into an Amazon side and a TPS side, and letting consumers choose the side they want. This separates the platform participants into two groups: the Amazon side with only the “core” competitively-priced products, which is chosen by high search cost consumers; and the TPS side with a greater product variety and higher prices, which is chosen by low search cost consumers who can benefit from the variety. Allowing consumers to make the choice between Amazon or “supporting small businesses” would improve TPS profits, allow Amazon to continue selling and address market power imbalance without harming consumer welfare.

The methodological contributions of the paper are worth noting. I derive estimating demand equations of the form: consideration set probability multiplied by demand conditional on the consideration set, all summed over the possible consideration sets. This form is shared by a wide class of papers studying demand estimation under limited consideration (e.g., [Goeree 2008](#)). However, my consideration set probabilities are *structural* objects, as opposed to the *reduced-form* consideration set probabilities typically used in the literature. This allows me to take into account how consumers will re-optimize their search in response to counterfactual situations. I construct them from an optimal sequential consumer search process over the arrangement of products, where navigation of the platform is conceptualized in tree-form. Solving for the optimal path along a branching tree can be complex, but I provide a tractable solution and estimation method. The additional data requirement is minor once optimality is applied—publicly observable data on the distribution of product arrangements is sufficient. This keeps my methodology within the class of demand estimation techniques that utilize aggregate market data. The additional structure is compatible with, and can supplement, existing demand estimation methods (i.e., it nests full consideration models). Here, I use the classic nested-fixed point algorithm ([Berry, Levinsohn and Pakes 1995](#)), but I augment it with an optimal consumer search solution process. It is product price and position variation across time that pins down the fundamentals parameters of the model: (i) distribution of consumer preferences and search cost, (ii) unobserved product quality and (iii) product marginal costs.

While existing methods rely on reduced-form assumptions to address the large combinatorial problem of consideration sets (and/or use micro-data to observe the consideration set directly), my model instead uses consumer search optimality and the observable distribution of the product arrangement. This allows me to sum over only the possible consideration sets implied by the optimal search path instead of the power set of products as in reduced-form consideration set probabilities. I also recover the joint distribution of consumer search cost and price sensitivity, and their correlation.

1.1 Literature and Contributions

Methodologically, this paper adds to the demand estimation tools in the limited consideration literature and answers questions asked in the growing search design literature about how firms influence the consumer search process. It also provides results relevant for understanding antitrust issues for online retail platforms and should also be of interest to the platform design literature.

The consumer search literature has its roots in theoretical work by [Stigler \(1961\)](#) and [Stahl \(1989, 1996\)](#), which sought to explain the existence of price dispersion in otherwise homogeneous goods by developing tools to include consumer search. Solutions to the more general differentiated goods consumer search problem was studied by [Weitzman \(1979\)](#) and [Hauser and Wernerfelt \(1990\)](#). This was followed by empirical estimation of demand under limited consideration for homogenous goods that demonstrated the importance of accounting for search to arrive at accurate demand estimates ([Hortaçsu and Syverson 2004](#); [Hong and Shum 2006](#); [De los Santos, Hortaçsu and Wildenbeest 2012](#)). Building on this work, the modern empirical literature asks a broad variety of limited consideration questions in the differentiated goods setting ([Goeree 2008](#); [Moraga-Gonzalez, Sandor and Wildenbeest 2015](#); [Jacobi and Sovinsky 2016](#); [Honka and Chintagunta 2017](#); [Dinerstein, Einav, Levin and Sundaresan 2018](#); [Murry and Zhou 2020](#)).

My paper is closest to [Dinerstein, Einav, Levin and Sundaresan \(2018\)](#), who study how platforms can affect consumer search. They analyze the eBay platform using both experiments and structural estimation of demand under limited consideration.⁵ I build upon this work by endogenizing the search process, modeling the more complex arrangement of products used by the Amazon platform and examining the implications of such an arrangement. A key component of my research question is the competition between the platform owner and seller participants, a force not present on eBay.

This question of how firms and platforms influence search is an area of ongoing work. [Hodgson](#)

⁵[Dinerstein et al. \(2018\)](#) also develop a search model in their appendix. The search model differs in being able to capture both the search results and BuyBox features of the Amazon platform.

and Lewis (2019) develop a Gaussian Process model of product search and ask if platforms change search costs to influence the updating of consumer beliefs. In their estimation, products have the same (distribution of) cost that must be paid, and this cost is varied in their counterfactuals. Here, I estimate my model taking into account how the platform increases the costs of searching some products and decreases it for others (i.e., search results), before varying it in counterfactuals. They focus on belief updating, while I assume rational expectations. Gardete and Hunter (2020) develop a dynamic discrete choice framework with consumer beliefs to study how an online car dealer's arrangement of products and product characteristics affects consumers' search decisions and outcomes. Lee and Musolf (2021) study self-preferential behavior in Amazon's BuyBox and whether it contributes to barriers to entry. They find evidence of self-preferencing and show that it improves consumer welfare in the short run, with long-run entry effects offsetting the gain. My paper differs in two main ways. (i) Their consumers choose between homogeneous products sold by differentiated firms (i.e., BuyBox level), while my consumers choose between differentiated products sold by differentiated firms (i.e., search results level). This allows me to study how Amazon's search design influences how they and TPSs compete for consumers with heterogeneous taste across the price-quality spectrum. (ii) Apart from similar demand and supply components, they model firms making optimal entry decisions (based on entry costs) while I model consumers making optimal product search decisions (based on consumer search costs). Thus firm entry reoptimization is the key force in their model. In my paper, consumers reoptimize their consideration set formation in response to changes in the expected value from searching, this is the key innovation. Teng (2021) examines self-preferential behavior in Apple's App Store search results and how it affects consumer search and firm app quality investment. She finds that eliminating preferential behavior increases investment of independent apps and improves both consumer and producer surplus. There, the model of consumer search builds upon Weitzman (1979) with modifications appropriate to the Apple App Store setting. My Amazon setting necessitates a search model where consumers exert effort to reveal information presented at the search results stage (see the Weitzman (1979) discussion below).

As previously mentioned, I derived demand equations broadly similar those estimated by Goeree (2008), and posed as early as Manski (1977), but my considerations sets form from optimal search behavior. Existing approaches have focused on identification and recovery of demand parameters while taking a comparatively agnostic stance about the consumer search process. Abaluck and Adams-Prassl (2021) exploit the asymmetry of cross-characteristics responses to show the identification of demand for two classes of consideration set probabilities. Abaluck and Compiani (2020) use cross derivatives to estimate demand in a way that is robust to various forms of consumer

search in settings where there are hidden attributes that consumers search for. [Amano, Rhodes and Seiler \(2018\)](#) provide a method to use data on search behavior to estimate demand in settings with a very large number of products. However, my questions require recovering consumer search costs and seeing how consumers will re-optimize their search when changes are implemented to the product arrangement. Therefore I pose an explicit optimal consumer search model that also determines the form of my consideration set probabilities.

It is worth mentioning a point of difference to the rich set of [Weitzman \(1979\)](#)-style papers, which feature explicit search models. There, a consumer starts with some component of utility (e.g., part of the product characteristics) in hand for a fixed set of products. They then choose an order of products to *search*, which is an action that reveals the remaining component of utility (e.g., utility shock) and adds the product to the consumer’s consideration set. The revelation of the remaining utility is the focus of search in such papers.

In contrast, my consumers begin at an “earlier” stage with neither a component of utility in hand nor a fixed set of products. Rather, they can choose to engage in *search*, which is an action that navigates the platform (e.g., sequentially reveal parts of an arrangement of products), and they can add products to their consideration set in the order the platform provides them. Consumers make their search decision based on rational expectations of the products (and their characteristics) that the search will bring. In my setting, the majority of pertinent information, including the price, star rating, shipping and picture, is revealed at the search results stage. Thus, consumers in my model expend effort to reveal critical information like price, rather than residual utility. At the same time, due to lack of micro data, I do not estimate the later stage of searching further for information (e.g., worded reviews). Since the most direct way in which platforms influence search is choosing product arrangement in the search results and the BuyBox stage, my modeling approach is necessary to answer my question. Other papers have demonstrated the importance of the different stages of search, for example [Honka, Hortaçsu and Vitorino \(2017\)](#) show that advertising in the US banking industry is a shifter of “awareness” as opposed to “consideration”.

Another point of difference worth noting is that [Weitzman \(1979\)](#)-style papers allow an unrestricted search order, while here the platform’s product arrangement “power” restricts the order in which products can be added to a consumer’s consideration set (i.e., semi-directed search). My approach contributes to the growing use of search results data; for example, [Ursu \(2018\)](#) uses search results data from Expedia to provide causal estimates that show the position of a product in the search results affects search and does not affect utility. The author also employs a [Weitzman \(1979\)](#) model with search results position added as a search cost shifter. My model builds upon this by exploiting the additional richness of product arrangement data, which enters my model

structurally as the (restricted) space over which search occurs.⁶

Additional papers focus on other “stages” of search. [Koulayev \(2014\)](#) and [Chen and Yao \(2017\)](#) use clickstream data to study the use of search refinement tools and establish their importance for their contexts. I expect the use of these tools to be minimal in my context of simple-to-understand and low-stakes household products.⁷

I also contribute to the rich set of papers that shed light on the Amazon platform. [Chevalier and Goolsbee \(2003\)](#) developed estimation of market shares from sales ranking data, which I utilize and augment with additional data for this paper. [Kim, Albuquerque and Bronnenberg \(2010, 2017\)](#) derive consideration set probabilities using “also-viewed” data for Amazon, showing that it is possible to utilize this aggregate form of “clickstream” data to estimate [Weitzman \(1979\)](#)-style search. I differ from this research by modeling how the platform influences and restricts search through the search results and BuyBox, and show that this arrangement meaningfully affects firm and consumer outcomes.⁸ [Morozov \(2019\)](#) uses clickstream data to estimate a model of limited consideration and costly search using Bayesian methods, and show that improving limited consideration would increase consumers’ ability to benefit from innovative products.

Lastly, I note a rich literature of approaches to solving consumer search problems, with both similarities and differences from my approach that are attributable to the different specifics of search being modeled. [Weitzman \(1979\)](#) derives the classic reservation-value approach; [Chade and Smith \(2006\)](#) solve for a general portfolio selection problem; [Fershtman and Pavan \(2021\)](#) and [Greminger \(2021\)](#) solve the search and consideration set formation process by representing it as a multi-armed bandit problem; and [Gardete and Hunter \(2020\)](#) utilize a dynamic discrete choice framework to model the sequential process. My approach resembles some of these approaches, reflecting a common use of optimal search. Overall, I simplify the problem and tailor it to my question of search design in the Amazon context. Specifically, I conceptualize the product arrangement as a tree to match my data on product arrangement and build the sequential search process around it.

The remainder of the paper is organized as follows: [Section \(2\)](#) details the consumer search and firm pricing model; [Section \(3\)](#) discusses the data, descriptive statistics and reduced-form evidence;

⁶The difference in having the search results position enter the model as the space over which search occurs, rather than as a search cost attached to a product, is important. I provide two example implications. (i) My model features uncertainty in the products search will reveal. For example, a price sensitive consumer may search to the end of a list, expecting a certain chance of a low-price product, and not obtain it despite paying the cost of searching. (ii) The cost of revealing products is state-dependent in my model. For example, a price sensitive consumer may search to the end of a list and find two low-price products close together. In my model, they incur the initial high search cost and a small incremental search cost to add both to their consideration set. Under a search cost shifter in a Weitzman model, the same consumer would incur two instances of the high search cost to add both to their consideration set.

⁷On the Amazon platform, filtering on “low to high price” often leads to unsuitable products being populated in the search results (e.g., low price accessories or replacement parts for the product the consumer is actually interested in).

⁸The authors show that the recommendations shown in product pages are beneficial for consumers; I provide similar results for the search results ordering.

Section (4) covers estimation of the model; Section (5) discusses the estimation results; Section (6) uses counterfactual analysis to study market power and the effect of antitrust actions; and finally Section (7) concludes.

2 Model

This section introduces my model where consumers search over the arrangement of products and firms price in response to consumer search behavior. Consumers in the model decide sequentially whether they want to see additional products, taking into account what products they have already seen, what products they expect to see and their own taste preference and search costs. The model clarifies how product arrangement (i.e., platform search design) influences the consumer search process. It provides micro-foundations for the probability of forming consideration sets, leveraging existing assumptions in standard random utility choice models. For the purposes of estimation, it is compatible with standard aggregate-market-share demand estimation techniques (i.e., BLP). The resulting consideration set probabilities are structurally derived (and closed-form), as opposed to the reduced-form consideration set probabilities commonly employed in the literature.

There are two sets of agents in the model: firms (Amazon and a large number of Third Party Sellers (TPSs)) with products $j \in J$ and consumers $i \in I$ who are heterogeneous in search costs (i.e., cost of time) and tastes for products.

The model is a two-stage game, with additional substages for the consumer search problem:

1. Firms with products $j \in J$ set prices p_j to maximize profits.⁹
2. Consumers $i \in I$, in a sub-game detailed below, choose whether to search on the platform or not, search sequentially (navigate the product arrangement) to expand their consideration sets and make a purchasing decision.

The model is static (one-shot), uses Subgame Perfect Nash Equilibrium as the solution concept and is solved by backwards induction. For ease of exposition, I introduce the model under full information (i.e., consumers know the arrangement and product characteristics of the products), but give consumers rational expectations when taking the model to estimation. Specifically, consumers are given the empirical distribution of the observed arrangement of products and form rational expectations using that information.

This means that I do not model the updating of consumers beliefs and learning over time. Rather, the reason consumers in the model engage in search is to reveal uncertain products and

⁹To simplify notation, I do not use separate subscripts for firms and products. However, in the empirical setting there are many firms selling the exact same product (SKU or UPC). In estimation, j should be thought of as a product-firm combination, where a firm sets prices simultaneously for all the products it controls.

their characteristics (both price and non-price characteristics), and to expand their consideration set. Models focusing on beliefs typically omit search for price and non-price characteristics, and the trade-off would not be worth it in my setting. Consumers are searching for products that fit their heterogeneous tastes and can readily determine their utility for a product once seen. They are not expending effort to understand their taste or to change their beliefs about what products might be on the platform. This allows me to focus on the first-order and direct impact of the platform owner’s chosen product arrangement, which is substantial in this setting.¹⁰ The omission of belief updating and learning is due to the lack of micro-data that would pin down such mechanisms and the minor role it plays in the straight-forward products of “Home & Kitchen” products.¹¹

I will refer to Amazon as “the platform” and treat other online retailers/platforms as a composite outside option denoted as “the other platform” or “another platform”. The following subsections tackle the consumer and firm stages in reverse.

2.1 Consumers’ Problem

Consumers have unit-demand to purchase a product in a particular category (e.g., waffle makers) online. They are heterogeneous with respects to their search costs s_i , drawn from distribution F_s and may also be heterogeneous with respects to price sensitivity or tastes for product characteristics in a way that is correlated with search costs. The timing for consumer i is as follows:

1. Choose between the platform, or one of two outside options: not searching (and consequently not purchasing) or another platform (i.e., a composite choice of other online retailers/platforms).
2. Upon choosing the platform, the consumer obtains an initial set of products (i.e., they go to the platform’s website, use the search function and are provided with search results; products at the top of the search results that are visible on the computer screen enter their consideration set).
3. The consumer may choose to search to expand their consideration set by sequentially navigating the platform (e.g., choose to scroll down the search results to reveal more products).
4. At some point, the consumer find it optimal to stop searching. They will consider the products in their consideration set, realize taste shocks, and choose one (or none) to purchase.

¹⁰The markets that I study (see [Section \(3\)](#)) are chosen accordingly; they are everyday Home & Kitchen products that consumers do not require significant learning about and for which they are unlikely to invest too much time in searching for. These markets are rich with a large number of comparable high-quality products, and rich with differentiated goods. It is exactly these markets which the platform’s power to influence search would be the strongest.

¹¹My framework can be augmented with micro-data to allow the model to capture the effects of consumers updating beliefs.

2.1.1 Purchase Stage

Working backwards, after search stops, consumer i examines the products in their consideration set \mathcal{C}_i , receives i.i.d. ϵ_{ij} taste shocks for each $j \in \mathcal{C}_i$ and chooses the product that provides the greatest utility (or decides to not purchase, as \mathcal{C}_i always contains no purchase $j = 0$). At this stage, this is a standard random utility discrete choice model, conditional on the consideration set \mathcal{C}_i formed in the search stage. The indirect utility for consumer i from purchasing product j is given by:

$$u_{ij} = \underbrace{-\alpha_i p_j + X_j' \beta_i + \xi_j}_{\delta_{ij}} + \epsilon_{ij} \quad ,$$

where p_j is the price of product j , α_i is the individual-specific price sensitivity, X_j' is the vector of observable attributes about product j , β_i is the vector of associated taste coefficients which could be individual specific, and ξ_j is the (unobserved to the econometrician) scalar product j quality. Following standard discrete choice models, the probability of a consumer i choosing product j from their consideration set \mathcal{C}_i is given by:

$$P(i \text{ chooses } j | \mathcal{C}_i) = P(\delta_{ij} + \epsilon_{ij} > \delta_{ij'} + \epsilon_{ij'} : \forall j' \neq j \wedge j, j' \in \mathcal{C}_i) \quad .$$

Note that consumers only receive their i.i.d. ϵ_{ij} taste shock once they stop searching. This timing assumption is crucial for tractability. However, it is already an assumption that is implicitly made in all the papers with reduced-form consideration set probabilities that this paper builds on.¹² Specifically, any paper where demand is constructed from the consideration set probability multiplied by demand conditional on a consideration set, all summed over the possible consideration sets implicitly makes an equivalent timing assumption when invoking i.i.d. ϵ_{ij} shocks. To see this, note that if the realization of any product's i.i.d. ϵ_{ij} taste shock occurred before the purchase decision such that it influenced the formation of the consideration set (i.e., affected whether another product was in the consideration set), then the ϵ_{ij} taste shocks would immediately become correlated in some manner, making any invocation of i.i.d. ϵ_{ij} contradictory.

The timing assumption provides a level of separability between the search stage and the choice stage, which is the source of the tractability. As such, ϵ_{ij} can be interpreted as consumers learning their residual taste for a particular product once they have stopped searching and are actively making a purchasing decision. Note that ϵ_{ij} is not the only source of horizontal differentiation, as there is taste heterogeneity (reflected in the α_i and β_i parameters) and so there is also heterogeneous

¹²This includes [Goeree \(2008\)](#); [Dinerstein et al. \(2018\)](#).

behavior in the search stage. The demand stage is otherwise standard. I will now discuss the key part of the model—the search process.

2.1.2 Search Stage

It is convenient to model consumer search as the traversal across a tree-like structure consisting of nodes and edges. Nodes contain one or more products, and there is a traversal cost associated with moving to a previously unreached node. Landing on a node adds the products in that node to the consumer’s consideration set.

In my context of online retail platforms, you may think of a node as a particular screen of the platform’s website; for example, the initial set of products that you see on the computer screen after you type “waffle maker” into Amazon.com’s search bar. In turn, the traversal cost would be the cost of scrolling down the search results and expending effort to examine the new product information contained on that screen. When consumers first arrive on a platform, they land on the root node of the tree (i.e., the initial screen of search results, [Figure 1](#)). They may then choose to move to nodes connected to nodes they’ve previously reached. The cost of traversal for a specific node only needs to be paid once, so it is costless to retrace steps. This is equivalent to the costless recall assumption in many search models and is realistic given online browsing behavior (e.g., the use of tabs for navigation).

Figure 1: Example of Search Results

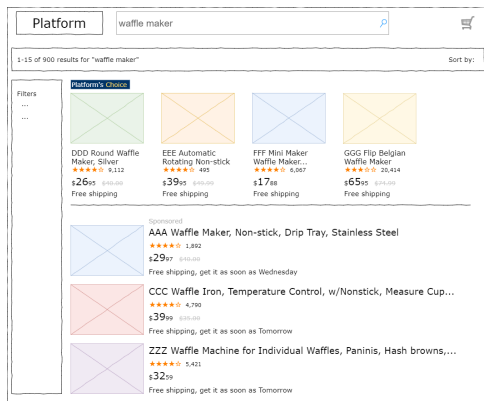
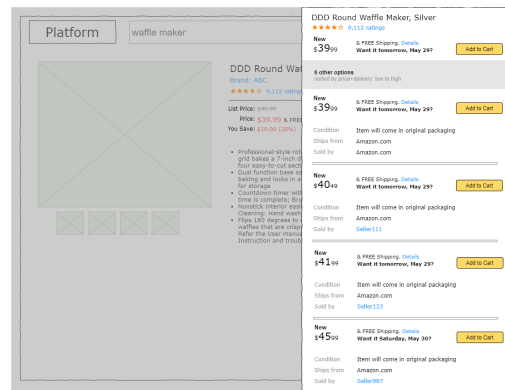


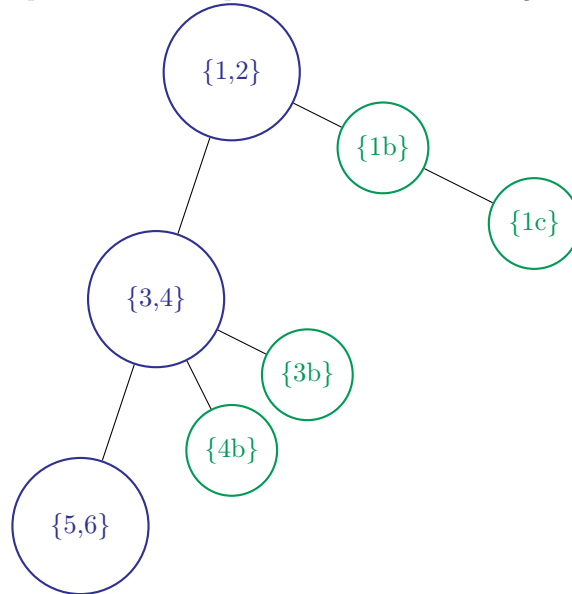
Figure 2: Example of BuyBox Grouping



Conceptualizing the arrangement of products in this way places informative restrictions on the possible consideration sets and, more importantly, eliminates consideration sets that are not possible. Specifically, it makes a strong assumption about the consumer search process that products that are “deep” in the tree could only be added to a consideration set after products that are “shallow” in the same branch have been added to the consideration set. Empirically, certain products are more likely to be placed in the first few screens of the search results, while other

products are never found on the first page of search results (see [Section \(3\)](#)). This means that products at the top of the search results compete with few competitors for the consumers who stop searching early, while those at the bottom of the search results are always considered alongside a larger set of competitors. My model incorporates this specific distribution of product arrangement as a model input as it is crucial for understanding how platform search design affects consumer and firm outcomes.

Figure 3: Example Tree-form Representation of the Arrangement of Products



This is a stylized example of the arrangement of products created by Amazon’s search results and BuyBox grouping as represented by a tree diagram consisting of nodes (the circles) and edges (the lines connecting the nodes). Products in the search results are represented by the numbers contained in the larger blue nodes, while the non-BuyBox sellers of the same product (i.e., SKU) are denoted by the letter suffixes contained in the smaller green nodes. The firm in the BuyBox has no letter suffix.

Modern platforms are a complex mass of linkages, and while my framework does not rule out such complexity, it would be infeasible to estimate a model that replicates all the links of a platform. Instead, I focus on the two most important ways in which the Amazon platform affects the consumer search process: the ordering of products in the *search results*; and the *BuyBox* grouping of products. While most consumers would be familiar with navigating the search results ([Figure 1](#)), the BuyBox grouping is less well known. Due to the low barrier to entry on Amazon, there are many sellers offering the same exact product (i.e., SKU) at any time. For the products studied in this paper (i.e. top selling products and products most likely to be shown to consumers), the BuyBox grouping selects the lowest-price seller to be “in the BuyBox,” which means that they are the default seller for all consumers. Consumers have no compelling reason to actively seek out additional sellers by navigating through to a “see additional sellers” link on the product page ([Figure 2](#)). Despite the search for non-BuyBox sellers being “off-path”, it is important to model them. The BuyBox seller (i.e., the default seller) for a particular product sets their price knowing

that the BuyBox grouping will reposition them if they raise prices sufficiently. This implies acute pricing pressure for some products, and this pressure is important to include for a counterfactual re-optimization of prices. An example tree that is illustrative of the search results and BuyBox grouping is provided (Figure 3). Note that conceptualizing navigation as traversal across a tree allows us to model both search results and the BuyBox in a consistent framework.

When reaching a node with the same product (i.e. same SKU/UPC) from another seller, the consumer only keeps the higher utility version of that product in their consideration set. This ensures consumers does not obtain additional ϵ_{ij} shocks by accumulating multiple instances of the same product in their consideration set; the ϵ_{ij} taste shock is interpreted as pertaining to the product, not the seller of the product. This is equivalent to leaving all products in, but restricting the ϵ_{ij} shocks of the same product to be equal.

2.1.3 Comparison to Weitzman

It is important to note how my model differs from Weitzman-style papers, which typically utilize “clickstream” data. Continuing the discussion in section 1.1, my model focuses on the earlier “stage” of the search process where information in the search results is revealed. For the question of platform search design, it is crucial to model what portion of the search results a consumer optimally chooses to see, which is not modelled in Weitzman approaches. On Amazon, the majority of the information relevant for making a decision (e.g., price, product image, star rating, delivery time and cost) is revealed in the search results. My consumers exert effort to reveal these characteristics. In a Weitzman model these characteristics are known with certainty for all possible products before search begins. Weitzman consumers exert effort to reveal the remainder of utility as this is the action that maps into “clickstream” data.¹³ For my research question, not modelling the effort exerted to learn information given in the search results would lead to biased measures of how the platform influences search by choosing the product arrangement. At the same time, because I lack “clickstream” data, I abstract from the incremental search for product information (e.g., reading customer reviews) that is relevant for complex products and other questions about search. The effects of the incremental search is relegated to the i.i.d. taste shock.

My modelling of search as navigation rather than examination of specific products has further implications. (1) My model features uncertainty in the products and product characteristics search will reveal. For example, a price sensitive consumer may search to the end of a list, expecting a

¹³It would be incorrect to simply modify a Weitzman model to have consumers not know the characteristics on the search results page and still use observations of clicks from the search results page into product pages to estimate the model. In reality, when Amazon consumers click on a product page, they do so knowing the characteristics like price and shipping costs with certainty.

certain chance of a low-price product, and not obtain it despite paying the cost of searching. (2) The cost of revealing products is state dependent in my model. For example, a price sensitive consumer may search to the end of a list and find two low-price products close together. In my model, they incur a high search cost and a small incremental search cost to add both to their consideration set. Under a search cost shifter in a Weitzman model, the same consumer would incur two instances of high search costs to add both to their consideration set.

2.1.4 Solution to the Search Process

For ease of exposition, I condition on and suppress the notation for all consumer heterogeneity (e.g., price sensitivity) except for search cost heterogeneity to focus on the search process. The notation for other aspects of consumer heterogeneity is reintroduced at the end of this subsection.

Consumers make their traversal decisions sequentially, such that at any point they take into account their current consideration set, the set of potential expected consideration sets and the associated search costs. Search costs are sunk given their sequential nature. At any stage of search, consumer i with current consideration set \mathcal{C}_i will add products to their consideration set to form a new consideration set $\mathcal{C}'_i \supset \mathcal{C}_i$, incurring traversal cost $t(\mathcal{C}_i, \mathcal{C}'_i) s_i$ if:

$$E_{\epsilon, j} \left[\max_j \{\delta_{ij} + \epsilon_{ij}\}_{j \in \mathcal{C}'_i} \right] - E_{\epsilon} \left[\max_j \{\delta_{ij} + \epsilon_{ij}\}_{j \in \mathcal{C}_i} \right] \geq t(\mathcal{C}_i, \mathcal{C}'_i) s_i$$

or $EU(\mathcal{C}'_i) - EU(\mathcal{C}_i) \geq t(\mathcal{C}_i, \mathcal{C}'_i) s_i$,

where the LHS is the expected utility gain associated with expanding the consumer's consideration set. The cost of traversal $t(\mathcal{C}_i, \mathcal{C}'_i)$ is the sum of the additional "base" traversal costs to get from \mathcal{C}_i to \mathcal{C}'_i and is multiplied by s_i to get the total search cost (i.e., consumers with higher search costs or higher cost of time pay multiplicatively higher costs to traverse). While $t(\mathcal{C}_i, \mathcal{C}'_i)$ could be a complex object, I assume that the traversal cost is the same for each step (i.e., from a previously reached node to an adjacent node) and use a free normalization to set the traversal cost between two adjacent nodes to $t(\mathcal{C}_i, \mathcal{C}'_i) = 1$. Thus, a consumer with search cost s_i pays s_i to move to the next "screen" of the search results. The consumer chooses to stop expanding their consideration set if there is no \mathcal{C}'_i for which the above inequality holds (i.e., no remaining beneficial search options).

It may seem that solving for the optimal sequence of searches across the tree for consumers with different search costs would be onerous. However, it is simple to show (see [Section \(A\)](#)) that it is sufficient to find the upper envelope of a set of affine functions, namely the Ex-ante Expected

Utility (ExEU) of all possible consideration sets (given the tree structure):

$$\text{ExEU}(s; \mathcal{C}) = \text{EU}(\mathcal{C}) - t(\{0\}, \mathcal{C}) s \quad .$$

The Ex-ante Expected Utility of a consideration set is the expected utility of that consideration set less the total costs of traversal from a consideration set of just the outside option to the consideration set in question.¹⁴

Importantly, the resulting upper envelope of $\text{ExEU}(s; \mathcal{C})$ for all possible \mathcal{C} characterizes the optimal search path for all consumers. Denote this optimal set of consideration sets whose affine functions form the upper envelope as \mathcal{C}^* . Let this set of consideration sets be ordered (h) by the order in which they form the upper envelope from *right* to *left*, so that: $\mathcal{C}_1^* = \{0\}$; \mathcal{C}_2^* gives the set of 0 and the products in the root node; \mathcal{C}_3^* is the set of \mathcal{C}_2^* plus the set of products from the optimally chosen first node to search; etc. Note that $\mathcal{C}_h^* \subset \mathcal{C}_{h+1}^*$, and this gives the sequence of consideration sets reached by the optimal search path.

Intuitively, once we have conditioned on all consumer heterogeneity except for search costs, this mass of consumers' optimal search paths differ only by the “depth” of their search. By construction, there are kinks in the upper envelope. Denote the search cost s at the kinks (i.e., where the consumers are indifferent between searching further or not) as thresholds H^* , similarly ordered right to left. These are the thresholds or cutoffs where consumers become indifferent to searching further. In particular, with these affine functions, the kinks are given by:

$$H_h^* = \frac{\text{EU}(\mathcal{C}_{h+1}^*) - \text{EU}(\mathcal{C}_h^*)}{t(\mathcal{C}_h^*, \mathcal{C}_{h+1}^*)} \quad .$$

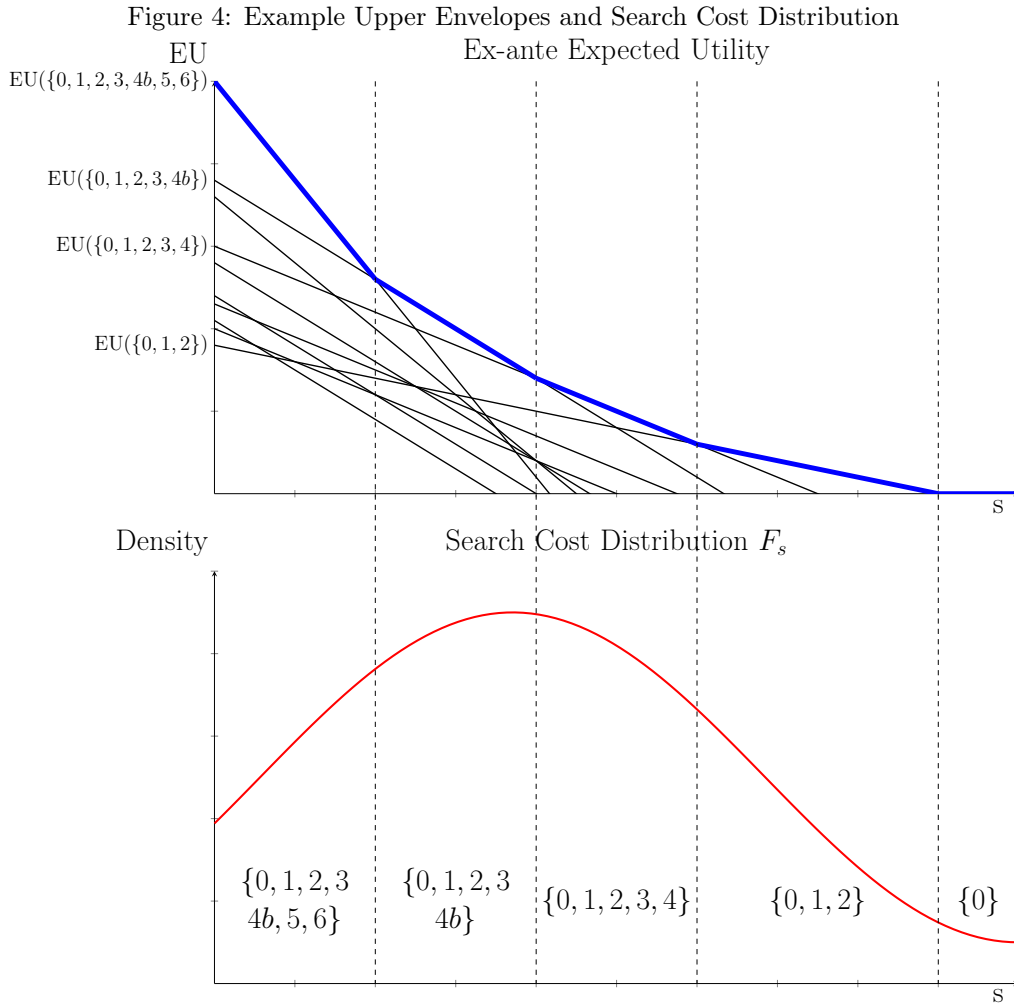
Note that I retain $t(\mathcal{C}_h^*, \mathcal{C}_{h+1}^*)$ here, since the optimal search path may “skip” a node such that the traversal cost is not necessarily just 1. This can occur when a node contains products that are low utility relative to products in the nodes beyond it, such that no consumers will choose to stop there (i.e., it would not form the stopping point of search for any consumer across the search cost distribution). Knowing the thresholds for the optimal consideration sets, it follows that the probability of each of the optimal consideration sets being formed in the population of consumers

¹⁴As is standard in upper envelopes of affine functions, this is implemented by finding the convex hull in the space of $\text{EU}(\mathcal{C})$ and $t(\{0\}, \mathcal{C})$ for every possible consideration set.

can be found by integrating over the distribution of search costs:

$$P(C_h^*) = F_s(H_{h-1}^*) - F_s(H_h^*) \\ = F_s\left(\frac{EU(C_h^*) - EU(C_{h-1}^*)}{t(C_{h-1}^*, C_h^*)}\right) - F_s\left(\frac{EU(C_{h+1}^*) - EU(C_h^*)}{t(C_h^*, C_{h+1}^*)}\right),$$

where $F_s(\cdot)$ is the CDF of the distribution of search costs (conditional on taste, suppressed) and the above equation represents the partitioning of the search cost distribution of consumers into their optimal consideration set. The solution that I describe above lends itself to a natural graphical representation (Figure 4).



This figure provides an example of the optimal search solution in graphical form. The top panel plots illustrative affine Ex-ante Expected Utility (ExEU) functions on the utility and search cost axes, while the bottom panel plots the search cost distribution. To avoid overcrowding the figure, not all of the ExEU functions are plotted on the figure. An ExEU function gives the value of a particular possible consideration set across individuals with different search costs. The intersection of any pair of ExEU functions gives the indifferent individual for that pair of consideration sets. The upper envelope of ExEU gives the optimal search path for this group of individuals, taking into account potential skips (i.e., instances where a node does not contain products that are sufficiently attractive for any individual to stop searching at that point). The vertical lines mark the kinks of the upper envelope and denote the indifferent individuals and thresholds. These show how the search cost distribution is segmented to give rise to the consideration set probabilities.

It follows that the probability of a particular product j being purchased (i.e., the demand when we have a unit mass of consumers) is:

$$P(i \text{ chooses } j) = q_{ij} = \sum_{\mathcal{C}_h^*: j \in \mathcal{C}_h^*} P(\mathcal{C}_h^*) P(i \text{ chooses } j | \mathcal{C}_h^*) \quad ,$$

which takes the common form: probability of a consideration set multiplied by demand conditional on a consideration set, all summed over the possible consideration sets. However, here the probability of a consideration set is not a reduced-form object as is common in the literature. For example, a reduced-form model might specify $P(\mathcal{C}) = \prod_{l \in \mathcal{C}} \phi_l \prod_{k \notin \mathcal{C}} (1 - \phi_k)$, where ϕ_l is the individual probability of product l being in *any* consideration set as a function of covariates and a statistical shock (often logit). Instead, in my model, $P(\mathcal{C}_h^*)$ is the solution to an optimal search process and does not include any additional statistical shock assumption. There are no exclusion restrictions or functional form restrictions (beyond assuming a search cost distribution) required to derive $P(\mathcal{C}_h^*)$. $P(\mathcal{C}_h^*)$ is a function of the search cost distribution, the existing demand parameters from the utility specification and the observed data on product arrangements.

On a practical level, the use of ϕ_l creates a form of independence between ϕ_j and $\phi_{j'} \forall j \neq j'$ that means that the joint probability of products being in a consideration set is restrictive and unlikely to reflect the true distribution. I show in [Section \(3\)](#) that certain products are consistently in worse positions and exhibit a joint-probability distribution that is not well represented by the use of independent ϕ_l 's.

Thus far, I have conditioned on all consumer heterogeneity except for search cost to simplify the notation, but it is straightforward to re-incorporate it. It is standard for the unconditional demand for product j to be written as the integral over the different types of consumer heterogeneity (here I consider heterogeneity in price sensitivity α). Choosing the order of integration and incorporating the optimal search results above, it follows that solving the consumer search problems provides the closed-form analytical integral over search cost heterogeneity. This means that while the search model adds a dimension of consumer heterogeneity in search costs, the computation burden of integrating over that dimension is lessened with the closed-form. Integrating over the remaining consumer heterogeneity can then follow standard demand estimation techniques (typically numerical intergration).

$$\begin{aligned} q_j &= \int \int P(i \text{ chooses } j) dF_s dF_\alpha \\ &= \int \sum_{\mathcal{C}_h^*(\alpha): j \in \mathcal{C}_h^*(\alpha)} P(\mathcal{C}_h^*(\alpha)) P(i \text{ chooses } j | \mathcal{C}_h^*(\alpha)) dF_\alpha \quad . \end{aligned}$$

Note that α affects the optimal consideration sets $\mathcal{C}_h^*(\alpha)$. While a group of individuals with the same tastes but different search costs will have one particular optimal search path (and differ in the depth at which they stop), another group of individuals with different tastes will have a different optimal search path and hence a different $\mathcal{C}_h^*(\alpha)$.

2.2 Illustrative Example

The example below illustrates how the model captures the market power generated by a particular arrangement of products with a simple 2-good example. Note that this simple 2-good example (i) abstracts from stochastic product arrangements (i.e., the lack of uncertainty reduces rational expectation to full information), (ii) does not feature branching paths in the product arrangement and (iii) does not feature consumer taste heterogeneity (which would generate different search paths). All of these features are important and present in the full estimated model. Nevertheless, this simple model provides the key intuition about the economics of platform search design. Assume that ϵ_{ij} is Type 1 Extreme Value and note that this functional form assumption yields:¹⁵

$$P(i \text{ chooses } j | \mathcal{C}_i) = \frac{\exp(\delta_{ij})}{1 + \sum_{j' \in \mathcal{C}_i} \exp(\delta_{ij'})}$$

$$\text{EU}(\mathcal{C}_i) = \log \left(\sum_{j \in \mathcal{C}_i} \exp(\delta_{ij}) \right) .$$

Let indirect utility be comprised of price p_j and vertical quality ξ_j so that $\delta_j = -\alpha p_j + \xi_j$. Consider the case where there is a single product per node. Denote the firm placed in the root (first) node as firm 1 and the firm placed in the second node as firm 2. Additionally, allow there to be a distribution of search costs $s_i \sim F_s$.

Using the results from above, demand for firm 1 and firm 2 are given by, where I denote $e_j = \exp(-\alpha p_j + \xi_j)$:

$$q_1 = \underbrace{[F_s(\log(1 + e_1) - 0) - F_s(\log(1 + e_1 + e_2) - \log(1 + e_1))]}_{\text{probability of } \{0,1\} \text{ consideration set}} \times \underbrace{\frac{e_1}{1 + e_1}}_{\text{monopoly}}$$

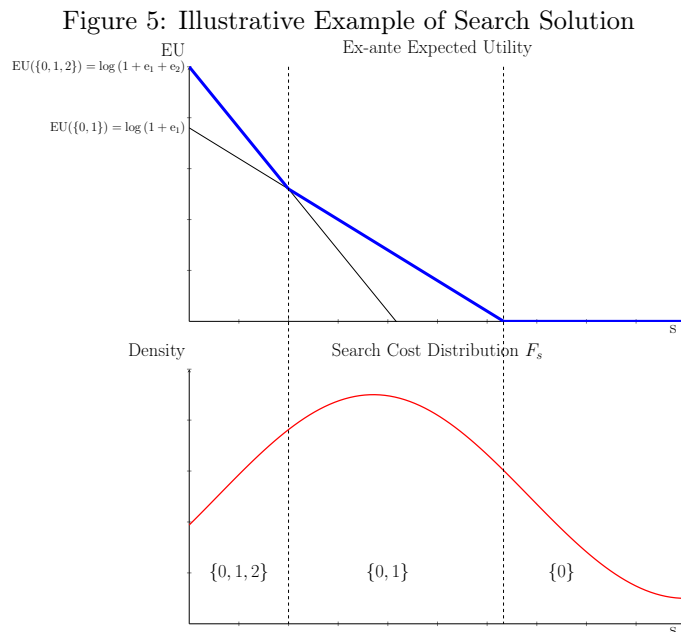
$$+ \underbrace{[F_s(\log(1 + e_1 + e_2) - \log(1 + e_1)) - 0]}_{\text{probability of } \{0,1,2\} \text{ consideration set}} \times \underbrace{\frac{e_1}{1 + e_1 + e_2}}_{\text{duopoly}}$$

$$q_2 = \underbrace{[F_s(\log(1 + e_1 + e_2) - \log(1 + e_1)) - 0]}_{\text{probability of } \{0,1,2\} \text{ consideration set}} \times \underbrace{\frac{e_2}{1 + e_1 + e_2}}_{\text{duopoly}} .$$

¹⁵After normalizing $\text{EU}(\mathcal{C}_i)$ by the Euler-Mascheroni constant.

Here, firm 1 faces less competitive pressure than firm 2 (relative to the model under full consideration) due to its advantageous position afforded by the product arrangement. Consumers with sufficiently high search cost will optimally decide to not search beyond the root node (i.e., probability of $\{0, 1\}$ consideration set). For these consumers, firm 1 is almost a monopolist (i.e., only competing against the outside option).¹⁶ Firm 2 has access to fewer consumers (those with low enough search cost; probability of $\{0, 1, 2\}$ consideration set) and competes with firm 1 for those consumers. Indeed, one interpretation of the power to arrange products is that it grants the power to create mixtures of market structure. Under full consideration, this 2-good example is a straight-forward duopoly in differentiated products. With search and product arrangement, the platform transforms the 2-good market into a mixture of a monopoly and duopoly.

Figure 5 shows how the Ex-ante Utility functions and their upper envelope give the solution to the consumer search problem, how it relates to the search cost distribution and how it gives rise to the consideration set probabilities.



This figure provides the optimal search solution for the illustrative example. The intersection of the ExEU functions shows the indifferent consumers, from right to left, first those who are indifferent between not searching at all and those searching once, and then those who are indifferent between searching once and searching fully.

Naturally, the firms will adjust their prices in response to the chosen market structure. Here, firm 1 will be able to set their prices higher (relative to a standard duopoly) because of the additional market power conferred by being in a better position in the product arrangement. To the extent that there is taste heterogeneity (excluded from this simple example) that is correlated with search costs, firms will also be selling to different types of consumers (e.g., differently price-

¹⁶To be more precise, it is a monopolist for the infra-marginal consumers.

sensitive consumers).

2.3 Firms' Problem

The preceding section described the consumer search process and derived product demand equations (i.e., the demand side). The characterization of the firm's problem (i.e., the supply side) is comparatively straightforward. Firms set prices p_j (with the vector of prices denoted as \mathbf{p}) as in a differentiated Nash Bertrand equilibrium for the products that they control. Firms are assumed to have different constant marginal costs $c_j \sim F_c$ drawn from some distribution. This is appropriate for firms focused on reselling products produced by wholesalers, but abstracts from inventory or dynamic concerns. There is also a commission τ on revenue charged by the platform for each unit sold. Note that the platform sets a uniform τ for all products in a broad category, this is consistent with Amazon's published commission schedule (15% for Home & Kitchen products). Thus, they maximize profits by solving:

$$\max_{p_j} ((1 - \tau)p_j - c_j) q_j(\mathbf{p}) \quad .$$

The profit-maximizing markup will be a function of the price elasticity of demand:

$$\frac{p_j - c_j / (1 - \tau)}{p_j} = \frac{1}{|\varepsilon_j|}$$

$$\varepsilon_j = \frac{p_j}{q_j} \int \sum_{\mathcal{C}_h^*(\alpha): j \in \mathcal{C}_h^*(\alpha)} \left[\underbrace{P(\mathcal{C}_h^*(\alpha)) \frac{\partial P(j|\mathcal{C}_h^*(\alpha))}{\partial p_j}}_{\text{standard elasticity}} + \underbrace{\frac{\partial P(\mathcal{C}_h^*(\alpha))}{\partial p_j} P(j|\mathcal{C}_h^*(\alpha))}_{\substack{\text{chg. in consumer search} \\ + \text{chg. in BuyBox}}} \right] dF_\alpha \quad .$$

For firms that sell multiple products (e.g., Amazon), I use the analogous multi-product first-order conditions with the associated cross-price elasticities. Additionally, I assume that the objective function of Amazon as a seller does not take into account the commission that it receives from TPSs. This is effectively assuming there is an "Amazon retail sales department" that operates separately from the "Amazon platform department". Given public reporting about the targets Amazon sets for its sales department, which aim for growth in their on-platform market share, it is reasonable that they set prices taking into account the cannibalization of third-party commissions.

As in the illustrative example above, note that the competitive pressure faced by firms depends on $P(\mathcal{C}_h^*(\alpha))$. If a product is placed "deep" in the arrangement of products, it will be in fewer

consumers' consideration sets, and will compete against a larger set of competitors. Products that are "shallow" within a platform's arrangement of products are in more consumers' consideration sets, and they are also competing against fewer firms for the consumers who engage in less search. Since consumers search based on expected product characteristics, a firm will set prices taking into account how it influences both the probability of consideration and the probability of choice conditional on consideration.

Note that I do not model firm entry and exit, nor the decision to advertise on the Amazon platform. I defer reoptimization of advertising and modelling of the ad auction for future work. The extension is natural given the foundation I provide here for the value firms should place on specific positions. These are not important for answering the positive economic questions, but could be of relevance for longer term outcomes for the normative economics questions.

3 Data and Reduced-Form Results

This section introduces the data used for estimation and provides descriptive and reduced-form results that establish the importance of platform search design.

I use publicly observable data scraped from the US Amazon website for 15 weeks in 2020 (July to October). The data covers 58 separate markets from Amazon's predefined categories of Home & Kitchen goods (e.g., toasters, air fryers, humidifiers and digital picture frames).¹⁷ Thus, a market is a collection of differentiated products (e.g., AmazonBasics toaster and Hamilton Beach toaster) sold by differentiated sellers. The markets are pooled for the reduced-form analysis but are treated separately for structural estimation.

For each market, the scrapers navigate the Amazon website and mimic a consumer searching on the website. The scraper submits a search query for the market (using keywords typically used by consumers per SEO data) and navigates through the first three pages of the search results, into the product pages of the product shown, and into pages showing the non-BuyBox sellers. Along the way it records everything shown, including the typical product characteristics data. More importantly, it records novel information about the position of the products on the search results and their non-BuyBox sellers. Since the set of products shown by Amazon for a particular search is stochastic, the scraper collects information around 30 times each week to obtain an empirical distribution of search results that will be taken as the true distribution for analysis. In this paper I use aggregate information on product market share and search results. Nevertheless, the model can incorporate individual purchase data and personalized search results. Conversations with Amazon

¹⁷Additional details, including the full list of the markets and their selection criteria are provided in [Section \(B\)](#).

economists confirm personalization of search results is limited and uses information from past recent purchases from the same category of goods. Importantly, they do not tailor to consumer demographics or other information due to the potential for negative public reactions. The markets studied here are infrequently purchased durables which are unlikely to involve repeated purchases. Thus the aggregate search results I collect should be representative of the search results seen by consumers.¹⁸

I aggregate the high frequency data to the week level, where appropriate. The primary unit of observation is therefore at the product-week jt level. I provide results for all observations and subsets, including the (on average) top 20 products in each market that forms the structural estimation sample. In such instances, the 20 products, 58 markets and 15 weeks together give $j = \{1, \dots, 20 \times 58\}$ and $t = \{1, \dots, 15\}$.

I provide summary statistics below (Table 1). Note that Amazon accounts for around one-third of products in the estimation sample and half of top selling products. Essentially all sellers (97%) use Amazon’s fulfillment services (i.e., Amazon Prime Shipping) and do not charge for shipping, thus there is little variation in shipping times across products.

Amazon sells products in the mid-price and mid-quality region of the product space, while TPSs sell fringe (low-price, low-quality or high-price, high-quality) products. Consistent with this, TPS products have higher price dispersion. Our chosen product markets are mature, high volume home and kitchen durables. There is an abundance of products in these markets and little dispersion in platform star ratings for the products observed in the first 3 pages of search results. The maturity of the market is also reflected in the average number of reviews being in the thousands. The ability of Amazon to influence consumer search is strongest in these markets (e.g., no lemons that limit the ability of Amazon to choose between products).

¹⁸While personalization of search results does not occur in the markets I have selected, using this methodology in other settings may lead to biased estimation results. For example, if a platform tailors the search results to match the user’s price sensitivity preferences, a model using aggregate search results would likely underestimate search costs and have uncertain biases with respect to price sensitivity estimates. Products that appear to the econometrician as being difficult to access may actually be easily accessed by consumers due to personalization, and subsequently purchased. This would lead the model to produce search costs lower than the truth to rationalize the purchase of those products.

Table 1: Summary Statistics - Products in Search Results

Characteristic	Product-Week Level					Market-Week Level
	Structural Sample	All	All Amazon	All TPS	Top 10	All Markets
Price (\$)	67 (71)	72 (140)	84 (107)	69 (149)	61 (62)	80 (59)
Position in Search Results	29 (18)	51 (22)	34 (21)	45 (21)	19 (16)	51 (7)
Sales Ranking	37 (122)	137 (329)	57 (134)	161 (360)	5 (3)	98 (123)
Sold by Amazon	36%	24%	100%	0%	52%	NA%
Shipped by Amazon	97%	94%	100%	92%	98%	NA%
Stars (/5)	4.50 (0.27)	4.43 (0.38)	4.51 (0.24)	4.40 (0.42)	4.55 (0.20)	4.44 (0.15)
1-Star (%)	4.8 (4.6)	5.6 (7.1)	4.5 (4.0)	5.9 (7.8)	4.0 (2.7)	5.4 (2.1)
No. of Reviews	6,068 (12,660)	3,507 (10,759)	7,064 (16,637)	2,273 (7,160)	13,558 (21,598)	3,796 (3,012)
Has Non-BuyBox Sellers	73%	63%	84%	53%	77%	NA%

¹ Mean (SD); %

² Sample for structural estimation is a selection of the (on average over the period) top 20 products

³ All products refers to all products observed in the first 3 pages of search results

⁴ Market-week column first averages product-week observations within a market and then averages the market-week observations

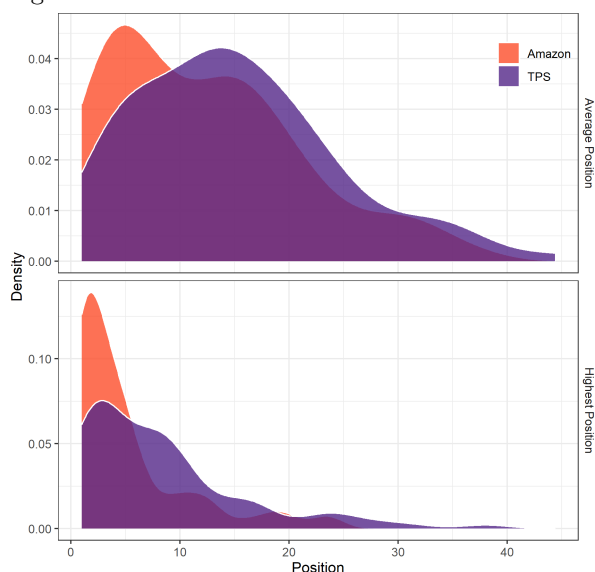
Given this paper’s focus on the search results and BuyBox grouping, I provide further metrics and reduced-form analysis about these features below.

3.1 Search Results

The search results determine the order in which consumers discover products and has important implications for the competition faced by the sellers of the products. Products that are more likely to show up at the top of the search results, and therefore be within easy reach, face fewer competitors than products. Conversely, products that are more likely to show up at the bottom of search results only get access to consumers with low search costs and compete with everyone above them for those consumers.

Aggregating observations over time, I calculate the average and “best” (i.e., minimum) position a product is assigned and examine its distribution across products, separately for those sold by Amazon and those sold by TPSs (Figure 6). Two takeaways are worth mentioning. First, products sold by Amazon (i.e., common brands and Amazon’s own brand products) are on average better positioned than products sold by TPSs. This may occur for a variety of reasons, including Amazon choosing to sell the more desirable products, which the search results algorithm then chooses to place in a better position. To establish whether this is beneficial or harmful to consumers, we need to consider an alternative arrangements of products where Amazon does not have this advantage. This requires estimation of the structural model introduced in the previous section. Second, many products do not ever attain a position in the first few “screens” of products (e.g., a position below 10). These products are only ever seen by low search cost consumers and compete against a larger set of products. The probability of considering a set of products is important in the model, and may be poorly represented by reduced-form consideration set probabilities.

Figure 6: Distribution of Positions Across Products

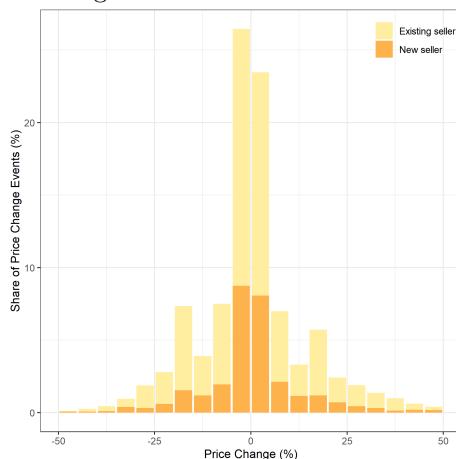


The top panel shows the distribution of the average position in which a product appears in the search results for that category of good, separated out by whether that product was sold by Amazon or TPSs. The bottom panel shows the same for the “best” position (where 1 is the best position) attained for the same. Only products that have appeared in the first page of the search results enough times to allow a reliable measure of their average and best are included in this calculation.

In order to estimate the parameters of the structural model (Section 4), we require variation in prices and variation in arrangements of products across time, which will likely depend on aspects of unobservable consumer demand. Price endogeneity stems from the reaction of firms’ pricing to consumer demand. Endogeneity in product arrangement can come from the platform responding to consumer demand by adjusting the search results ordering, or from firms advertising in response to consumer demand. I will use instruments in the structural estimation to address these sources of endogeneity, but it is nevertheless worth delving deeper into where the variation is coming from.

Around one-third of all price variation is associated with a new seller ending up in the BuyBox (Figure 7). This may happen for a variety of reasons, including a firm entering at a lower price point, or an existing firm exiting. Some of this may be exogenous variation. For example, some TPSs engage in “retail arbitrage”, where they purchase discounted products from offline retailers to sell on the platform (e.g., Walmart closes a store in one geographical area of the US and puts items on clearance that are bought by TPSs to sell on Amazon nationwide).

Figure 7: Variation in Prices

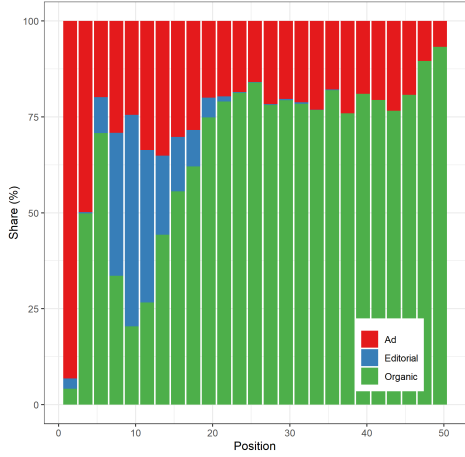


This figure shows distribution of the size and direction of price change events, broken down by whether that price change was also associated with a change in which seller ended up in the BuyBox. The majority of price change events do not result in a change in the BuyBox seller (“Existing seller”). For price changes associated with a change in the BuyBox (“New seller”), this may reflect a seller previously selling a product at a higher price now being the lowest price seller (e.g., due to a stockout) or a seller who has never sold the item entering at a price that places them in the BuyBox.

The search results are comprised of three types of listings: advertisements that are the result of ad auctions bid upon by the firms; editorials that are “curated” by the platform and sometimes reflect recommendations linked to independent product review websites; and organic listings that are generated by the platform’s search results algorithm. I do not include an advertising re-optimization stage in this paper, so my results cannot account for changes stemming from changes in incentives to advertise that would arise in the medium term. The costs of advertising are to some extent subsumed into the firm’s marginal costs and are not expected to change.¹⁹ Additionally, the equilibrium outcome is such that there is significant overlap in the products in the ad listings and the products in the organic search results. Within the top 50 positions, 80% of advertised products are also present in the organic listings. A product’s position in the search results will naturally vary within the organic listing, but can also vary due to firms changing their decision to advertise or the platform’s decision to make changes to its curation of products (Figure 9). These changes may reflect demand unobservables and this source of endogeneity will be addressed with instrumental variables.

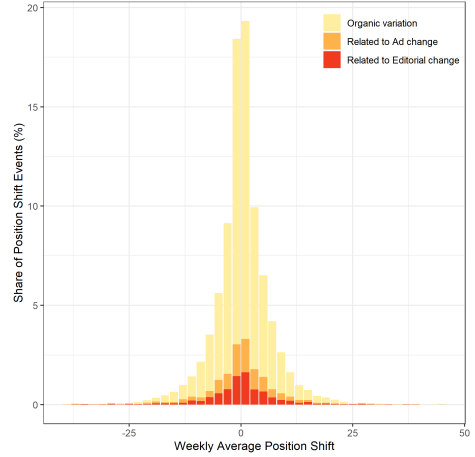
¹⁹Note that the BuyBox grouping takes precedent over the ad auction, meaning that a firm that is not in the BuyBox (not the lowest price) will not obtain an advertising slot no matter what it bids.

Figure 8: Search Result Listing Types



This figure shows the share of each listing type across the positions of the search results. Note that regardless of type of listing, they all contain the same amount of information (e.g., price, product image, star rating, shipping information). Ads dominate the first few positions and remain relevant and dispersed throughout the search results. Editorials are Amazon-curated suggestions that generally appear around the 10th position, and are distinct from ads by not being the result of an ad auction. The rest are organic search results that are generated by Amazon’s search results algorithm.

Figure 9: Variation in Positions



This figure shows the distribution of the size and direction of position change events, broken down by whether that price change was also associated with a change in the listing type, at the weekly average level. The majority of changes in position occur due to changes in the organic position of a product. The remainder of the position changes are associated with the products going from organic to advertised (and vice versa) and products going from organic to editorial (and vice versa).

Amazon reports a best-selling ranking for products in each market that is a reliable proxy for market share (Chevalier and Goolsbee 2003). The reduced-form analysis below uses this rank variable to establish the relationship between prices, search results positions and market share. In the structural estimation, I use estimates of market share derived from this rank variable and limited observations of inventory levels (see C).

I run a series of log-log regressions with product fixed effects (FE) to establish the relevance of the search results position for demand and to show that there is sufficient within-product variation of position and price:

$$\log(Y)_{jt} = \beta_1 \log(\text{Price})_{jt} + \beta_2 \log(\text{Position})_{jt} + \beta_3 \log(\text{Price})_{jt} \log(\text{Position})_{jt} + \text{ProductFES}_j + \epsilon_{jt} \quad .$$

Table 2: Correlation Between Sales, Price and Position

	<i>Dependent variable:</i>					
	Log(Rank)			Log(Sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Price)	0.037*** (0.006)	0.784*** (0.023)	0.784*** (0.074)	1.092*** (0.087)	1.358*** (0.098)	-1.391*** (0.165)
Log(Position)	0.808*** (0.006)	0.222*** (0.004)	0.222*** (0.019)	0.388*** (0.025)	1.263*** (0.209)	-1.552*** (0.254)
Log(Price)*Log(Position)					-0.103*** (0.024)	0.142*** (0.029)
Constant	0.734*** (0.054)					
Dep. Mean	3.83	3.83	3.83	2.43	2.43	3.18
Product FEs		Y	Y	Y	Y	Y
Market Clustered SEs			Y	Y	Y	Y
No. of Markets	58	58	58	58	58	58
Struct. Sample				Y	Y	Y
Observations	68,818	68,818	68,818	14,313	14,313	14,313

Note:

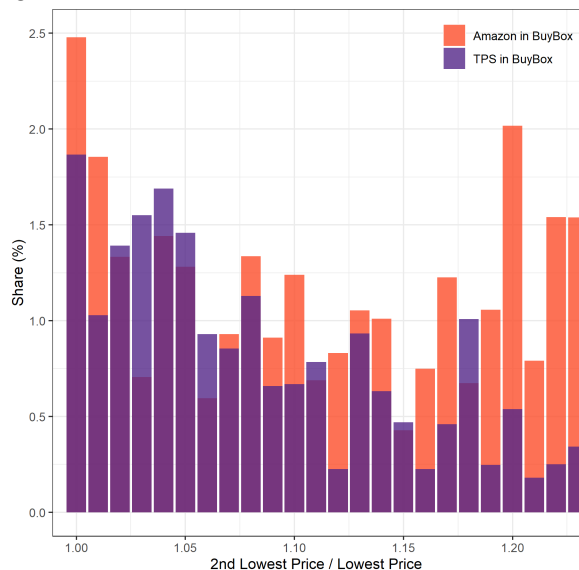
*p<0.1; **p<0.05; ***p<0.01

The regression produces significant coefficients estimates for price, search results position and their interaction, allaying potential concerns of multi-collinearity. The signs of the coefficients are as expected, where a rank of 1 is the best rank and a position of 1 is the best position. The interaction term coefficient is significant and suggests that products located at different positions in the search results face different price elasticity. This cross-variation will be important for establishing the correlation between consumer search costs and price sensitivity in the structural model. The last 2 column subsets to the structural estimation sample (i.e., the 20 products in each market) and finds consistent results. The final column uses the estimated sales numbers from the inventory data and displays reassuring consistency with the raw rank data (note that the reversal of the signs is mechanical and expected). Estimating the regression separately for each market leads to similar results for the subset of markets where there is sufficient variation to for accurate estimates (see [Figure 19](#)).

3.2 BuyBox Grouping

Amazon groups different sellers selling the same product (i.e., SKU/UPC) together and makes the lowest price seller the default for consumers to purchase from. This may create acute pricing pressure for the firm in the BuyBox (i.e., the firm with the lowest price), depending on the proximity of the second-lowest price. For a material share of products (5–10%), the second-lowest price is only a few percentage points above that of the lowest price (i.e., the leftmost bars in [Figure 10](#)). For these products, it is particularly important to account for the second-lowest price seller in the demand estimation.

Figure 10: Distribution of Positions Across Products



This figure shows the ratio of the second-lowest price to the lowest price (BuyBox price) for the same product. Incidences where the lowest and the second-lowest price are the same are not shown on the figure. The denominator includes the approximately 50% share of products that are only sold by one seller.

Consumers generally do not have any incentive to search the non-BuyBox sellers. There are exceptions where consumers could find lower prices among the non-BuyBox sellers (i.e., the default seller is not the lowest price). [Table 3](#) breaks down the reasons in instances where the BuyBox does not show the lowest price. Without accounting for non-price characteristics, around 3.3% of product-scrape level observations are exceptions where the lowest price is not in the BuyBox (column 1). However, taking into account whether the non-BuyBox seller has less than 100 reviews and their positive percentage being less than 97% brings the exception rate down to 1.2% (column 3). Further excluding instances where the price difference is less than 10 cents reduces the exception rate to 0.7% (column 4). The exceptions rate is a little higher for the structural estimation sample at 1.8%, since these products tend to have more non-BuyBox sellers (column 5).

Table 3: BuyBox Exceptions

	<i>Dependent variable:</i>				
	1(Exception) - Lower Price from Non-BuyBox				
	(1)	(2)	(3)	(4)	(5)
Constant	0.033*** (0.0001)	0.027*** (0.0001)	0.012*** (0.0001)	0.007*** (0.0001)	0.018*** (0.0003)
<100 Seller Ratings		0.109*** (0.0004)	0.055*** (0.0004)	0.046*** (0.0004)	0.067*** (0.001)
<97% Seller Positive			0.109*** (0.0003)	0.074*** (0.0002)	0.058*** (0.0005)
<50 cents diff				0.937*** (0.001)	0.936*** (0.002)
Dep. Mean	0.033	0.033	0.033	0.033	0.062
Struct. Sample					Y
Observations	3,021,373	3,021,373	3,021,373	3,021,373	770,714

Note:

*p<0.1; **p<0.05; ***p<0.01

Each observation is a product-scrape instance, the multiple points in time where the non-BuyBox information is collected. Around 27% of products do not ever have more than one seller and are always going to have the lowest price seller in the BuyBox.

4 Estimation

This section provides details on how the model described in [Section \(2\)](#) is estimated as well as the additional assumptions made to facilitate estimation.

For estimation, I specify the indirect utility of product j for consumer i at time t as follows:

$$u_{ijt} = -\alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} \quad ,$$

where p_{jt} is price, ξ_{jt} is unobserved quality and α_i is the individual-specific price sensitivity. Assume ϵ_{ijt} is distributed Type 1 Extreme Value. I opt to not include any other observable product characteristics. Note that product characteristics that do not change across time have their effects subsumed within ξ_{jt} (specifically the ξ_j component, introduced below in the discussion on endogeneity). Their exclusion does not affect the estimation of other coefficients as we are not interested in the heterogeneity of preferences for non-price characteristics. The platform's reported star ratings can change over time, but exhibit little variation in the sample given the mature nature of these categories.

I allow for two types of consumer heterogeneity: search cost s_i ; and price sensitivity α_i . Correlation between the two is permitted and important to capture. I assume the joint distribution to be bivariate normal:

$$(\alpha_i, s_i) \sim F_{\alpha, s} \left(\begin{array}{ccc} \mu_\alpha & \sigma_\alpha^2 & \rho_{\alpha s} \sigma_\alpha \sigma_s \\ \mu_s & \rho_{\alpha s} \sigma_\alpha \sigma_s & \sigma_s^2 \end{array} \right) .$$

The utility specification is standard (Berry et al. 1995), except for the addition of search costs that are correlated with taste heterogeneity. Indeed, the model can be estimated using a modified nested fixed point algorithm. First, note that the inner loop requires no modification. There is an inversion from market shares (q_{jt}) to mean utility (δ_{jt}), conditional on consumer heterogeneity parameters. These are typically the price sensitivity heterogeneity parameters (σ_α), but in this case also include the consumer search cost and correlation parameters (μ_s , σ_s and $\rho_{\alpha s}$). Conditional on consumer heterogeneity, the consideration set probabilities and search process defined above are only functions of product characteristics and unobserved quality. This means that inverted conditional utility is a function of the same parameters and data as under a full consideration demand model. In other words, the search process defined above augments the functional form assumption of demand, not utility itself. Thus, the model provides a search process that is compatible with standard utility assumptions.

Second, the solution for the optimal search path sits in the outer loop and must be computed for each parameter value. As is standard, price-sensitivity heterogeneity will be numerically integrated. I use Halton draws for my simulated individuals. To calculate the consideration set probabilities (the analytical integral over search cost heterogeneity), we need the empirical distribution of product arrangements (i.e., the observed search results and non-BuyBox sellers organized in tree-form).

Specifically, for each draw of product arrangement, I calculate all the possible consideration sets that can be formed by traversing the tree (i.e. the identities of the products, not their utilities, which vary with the parameters).²⁰ I use 100 draws of α_i price-sensitive individuals that are then expanded over the roughly 30 instances of trees observed per week, resulting in around 3000 simulated “individuals” per week of data.

4.1 Instrumental Variables

I address the endogeneity of ξ_{jt} by making appropriate time-series assumptions. Note first that allowing ξ_{jt} to be independent ($\xi_{jt} \perp \xi_{jt'}$) is unrealistic in my week-by-week setting, since we would expect the unobserved quality of products to exhibit a relatively stable relationship week-by-week. We should not expect a high-quality product in one week to become low quality the next week. On the other hand, the assumption that quality does not change ($\xi_{jt} = \xi_j$) may be too strong and rules out small demand shocks. Instead, I am allowing some fluctuations in the unobserved

²⁰This can be a highly combinatorial object, but note that I am focusing on two search design features, the search results and the BuyBox grouping, which generate trees that do not have too many branching paths.

product quality over time, and assume that it follows an AR(1) process.²¹ Specifically, I set:

$$\begin{aligned}\xi_{jt} &= \xi_j + \rho_{\text{AR1}}\xi_{jt-1} + \eta_{jt} \\ \implies \delta_{jt} &= -\alpha p_{jt} + \xi_j + \rho_{\text{AR1}}(\delta_{jt-1} + \alpha p_{jt-1}) + \eta_{jt} \quad ,\end{aligned}$$

where $\delta_{jt} = \xi_{jt} - \alpha p_{jt}$ and the second line follows from some algebraic manipulation of lag and contemporaneous periods. The product quality term has been separated into a stationary component ξ_j (which will be captured by the product indicator) and a contemporaneous component, the AR(1) shock η_{jt} . This assumption suggests natural instruments for addressing the price endogeneity problem. Lagged observables and lagged inverted utility are orthogonal to the remaining shock η_{jt} by assumption. In other words, in week t firms will react to the realization of the η_{jt} shock when they choose p_{jt} , leading to endogeneity. However, the previous week's price p_{jt-1} is not correlated with this week's shock η_{jt} . If we include product fixed effects (ξ_j), which pick up the stationary component of the AR(1) process, lagged price serves as a valid instrument.

I also require instruments to identify the search cost (and price sensitivity correlation) parameters of the model. Just as firms may choose price based on the contemporaneous AR(1) shock, the platform may choose the search result order based on the contemporaneous AR(1) shock, or a firm may engage in advertising for similar reasons. While the tree-form representation of the search results (embedded in the inverted utility δ_{jt}) may be correlated with η_{jt} , I can nevertheless use the lagged raw search results position pos_{jt-1} as an instrument (since pos_{jt-1} is itself correlated with the tree-form representation).

All together, the instruments lead to the following sets of moment conditions:

$$E \begin{bmatrix} \delta_{jt-1}\eta_{jt} \\ \{1(j=j')\eta_{jt}\}_{\forall j' \in J \setminus 0} \\ p_{jt-1}\eta_{jt} \\ \sum_{j' \neq j} (p_{jt-1} - p_{j't-1})\eta_{jt} \\ \text{pos}_{jt-1}\eta_{jt} \\ \sum_{j' \neq j} (\text{pos}_{jt-1} - \text{pos}_{j't-1})\eta_{jt} \\ p_{jt-1}\text{pos}_{jt-1}\eta_{jt} \end{bmatrix} = 0 \quad .$$

Looking at each (set) of instruments in turn, roughly speaking: the lagged inverted utility picks up ρ_{AR1} ; the vector of product indicators picks up the vectors of stationary components ξ_j ; the

²¹Lee (2013) makes a similiar AR(1) assumption in the context of a dynamic demand estimation problem.

lagged price picks up the μ_α ; the lagged price differentiation IV picks up σ_α ; the lagged search result position and its differentiation IV (Gandhi and Houde 2020) jointly picks up μ_s and σ_s ; and the interaction of lagged price and lagged search result position picks up $\rho_{\alpha s}$.

Identification—The intuition for identification of the parameters follows standard arguments. Broadly speaking, identification is given by price and product arrangement variation—the same variation demonstrated in Section (3). As in standard demand estimation, the price sensitivity and unobserved quality parameters can be identified from (endogenous) variation in prices across time. The addition of search and search cost parameters does not complicate this argument much. As search results positions do not enter into utility, the only way in which they affect market shares is through search and the consideration set probabilities.²² Thus, if we observe changing market share across time, but no changes in price, the only possible explanations are changes in unobserved quality of product or changes in product arrangement. The AR(1) assumption disciplines potential changes in unobserved quality, separating unobserved quality into a fixed effect and an idiosyncratic shock. The search component of the model determines how consideration sets change when product arrangement changes. In fact, the moments involving search results position exactly tease out which variation is responsible. In estimation, I start the model with zero search costs, at full consideration (which my model nests). At full consideration, if prices are not changing across time, changes in market share can only be rationalized by changes in unobserved quality (the AR(1) shock η_{jt}). However, if those changes in unobserved quality are correlated with (lagged) product positions, this indicates that the market share variation would be better explained by allowing there to be positive search costs. This is how the position moments push the model from full consideration towards a distribution of positive search costs where product arrangement leads to limited consideration.

The argument for identification of the standard deviation of search costs (separately from the mean) follows similarly from the arguments for identifying the standard deviation of price sensitivity. Under a random coefficient logit model, when a low-price product becomes a high-price product it loses its market share predominantly to other low-price products (rather than high-price products). This is because the standard deviation of price sensitivity allows there to be a segment of consumers who prefer low-price (and low-quality) products. The standard deviation of search costs governs how there are separate segments of individuals who search a little, and other segments that search intensively. This allows the model to explain how products at the top of the search results that move to the bottom of the search results lose their market share to

²²It is an assumption that the position of the product does not influence utility. This assumption has been tested, and shown to be realistic, by Ursu (2018) in the context of online travel booking.

products at the top of the search results. In the absence of a search cost distribution, where there is instead an identical search cost for all consumers, there would be a threshold before which moves in search result positions have no effect and after which no consumers would ever see the product (i.e., a cliff-like market share response). The correlation of price sensitivity and search costs is then identified from the differential market share changes of low-price products moving down the search results versus high-price products moving down the search results. In the case of negative correlation, a high-price product would mainly lose its market share to high-price products at the top of the search results, while a low-price product would lose its market share to low-price products at the top *and middle* of the search results. This is the negative correlation implies that the consumers preferring low-price products also tend to search more.

4.2 Additional Details

The estimation algorithm resembles standard nested fixed point demand estimation (Berry et al. 1995). Given a guess of the outer loop parameters $(\sigma_\alpha, \mu_s, \sigma_s, \rho_{\alpha s})$ and an initial guess of the inner loop parameters $(\mu_\alpha, \rho_{AR1}, \{\xi_j\}_{j \in J})$ we:

1. calculate α_i and the conditional distribution of s ,
2. calculate the utility for every possible consideration set that can be formed,
3. calculate the convex hull of the Ex-ante Expected Utility functions,
4. recover thresholds from kinks of the upper envelope of the Ex-ante Expect Utility functions and map these thresholds to consideration set probabilities,
5. integrate over individuals to obtain market shares q_{jt} ,
6. invert market shares to obtain inverted utility $q^{-1}(q_{jt} | \sigma_\alpha, \mu_s, \sigma_s, \rho_{\alpha s}) = \delta_{jt}$,²³
7. estimate inner loop parameters and obtain η_{jt} , and
8. iterate with a new guess of outer loop parameters based on the moments.²⁴

As noted before, I restrict the estimation to the top 20 products in order to focus on the most important elements of the consumer demand problem. Likewise, I restrict the estimation to include the non-BuyBox firm that has the lowest price (i.e., the firm with the second-lowest price) for each of the 20 products (if any). This is sufficient to replicate any pricing pressure for the BuyBox firm

²³Invertibility of the market share equation follows from Berry et al. (2013).

²⁴It is computationally burdensome to calculate gradients for the solution to the upper envelope (i.e., the search process). As such, I use gradient-free optimization algorithms to iterate.

to capture the firm’s pricing incentives. If a consumer chooses to search within the non-BuyBox firm (to the offshoot node) for a product j , their product j within their consideration set is replaced to ensure no duplication within the consideration set (i.e., consumers do not obtain another ϵ_{ijt} shock for a product they already have in their consideration set). The replacement contains the higher price of the non-BuyBox firm and an additional term γ_{jt} .

$$u_{ijt} = \begin{cases} -\alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} & \text{BuyBox} \\ -\alpha_i p_{jt, \text{non-BuyBox}} + \xi_{jt} + \gamma_{jt} + \epsilon_{ijt} & \text{non-BuyBox} \end{cases}$$

This term captures the net utility change associated with having the non-BuyBox product. I do not model the processes that generate γ_{jt} . For example, it can arise from taxation differences (e.g., a seller in California selling to a buyer in Texas does not charge sales tax, such that the total price may be lower for the non-BuyBox firm). Very few consumers are aware of this, it is applicable to a limited set of products and consumers, and it requires incurring extra search costs to confirm. Given the negligible market share of non-BuyBox firms, this preference specification does not have much effect on the demand estimates. Rather, its importance lies in the supply side, providing pricing pressure for BuyBox firms where appropriate.

Some additional details need to be discussed regarding the two outside options $j \in \{0, \text{other platform}\}$. Ideally, I would have detailed data about all products on all platforms. Instead, I follow the standard approach of aggregating purchases on other platforms under one outside option, the “other platform.” The “other platform” choice is made at the beginning of the consumer decision problem when consumers choose one specific platform. This effectively adds a starting branch to the tree that only permits one-way traversal.²⁵

I assume that the “other platform” is preferred by lower search cost consumers. Effectively, this incorporates a truncation assumption in the estimated distribution of search cost via the “other platform” choice. This is motivated by companion work where I show in a theoretical model that a separating equilibrium exists for two competing platforms. There, the non-dominant platform (e.g., eBay) chooses a more “laissez-faire” search design that is preferred by low search cost consumers, while the dominant platform chooses an aggressive search design (much like Amazon’s BuyBox) and caters to high search cost individuals. I therefore restrict the “other platform” to require a higher cost of traversal. By allowing consumers to first choose between the outside platform and the inside platform (and all its potential consideration sets), consumers are segmented based on their search costs.

²⁵While the model could allow for switching between platforms, incorporating this feature would greatly expand the size of the potential consideration sets that can be formed.

The market shares for the two outside options are an important input to the model. Industry reports commonly suggest that Amazon has around a 50% market share of online purchases, and available survey data show that conversion rates are high for consumers actively looking to purchase. I think of the market as being consumers who have unit-demand (e.g., they have decided to purchase a waffle maker, and are not just interested in collecting information), have decided to purchase online, are mainly choosing between what platform to search on and will do so in one “trip”. I think this is plausible for the markets considered, which are not so complex or expensive as to require repeated information gathering before purchase. I scale up aggregate sales data for eBay (observed for the corresponding market and weeks) to be an average 47.5% market share across weeks and assume that the no purchase share is the remaining average 2.5%. I will vary these numbers to evaluate sensitivity. It is important to keep these assumptions in mind when interpreting the results of counterfactuals where substitution between on-platform products and the outside platform or making no purchase is important.

5 Estimation Results

I discuss the raw results of estimation in this section. I present the results for one market (“waffle makers”) below.

The main parameters of interest are presented in [Table 4](#). The parameters are estimated imprecisely and fails poorly against individual testing of the null hypothesis of a zero coefficient. However, the more important question is whether the additional search component of the model is informative relative to the standard full consideration (i.e., no search) demand model. An LR-type test does reject the null hypothesis that full consideration is the true model (i.e. joint test that the search cost distribution lies entirely below zero) at the 10% significance level.²⁶ Inclusion of additional time periods and markets, which may address the noise in the estimates, is in progress.

Table 4: Main Parameter Estimates

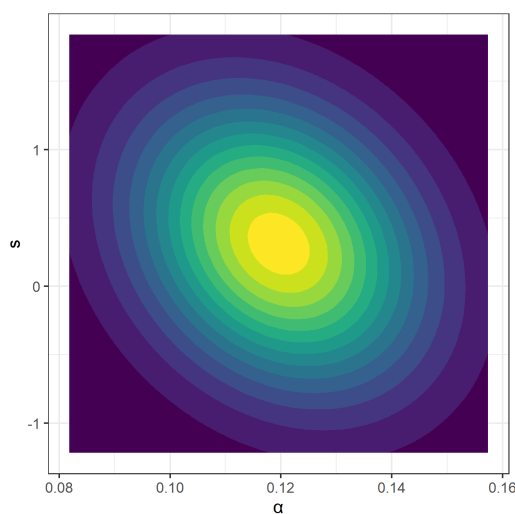
μ_α	0.120 (0.048)	μ_s	0.312 (0.094)	$\rho_{\alpha s}$	-0.239 (1.106)
σ_α	0.017 (0.061)	σ_s	0.696 (0.479)	ρ_{AR1}	0.257 (0.091)

Consumer heterogeneity is a key component of the model. It determines the consumer search process and, consequently, the types of consumers that firms sell to. [Figure 11](#) shows the bivariate normal distribution estimated by the model, which shows a negative correlation between search cost and price sensitivity. While different theories could motivate positive or negative correlations,

²⁶Specifically, I test the restricted model of $\mu_\alpha = -0.1, \sigma_\alpha = 0.01, \rho_{\alpha s} = 0$ against the estimated unrestricted model. I verify that the objective function value does not differ for alternate parameters of the search cost distribution consistent with full consideration.

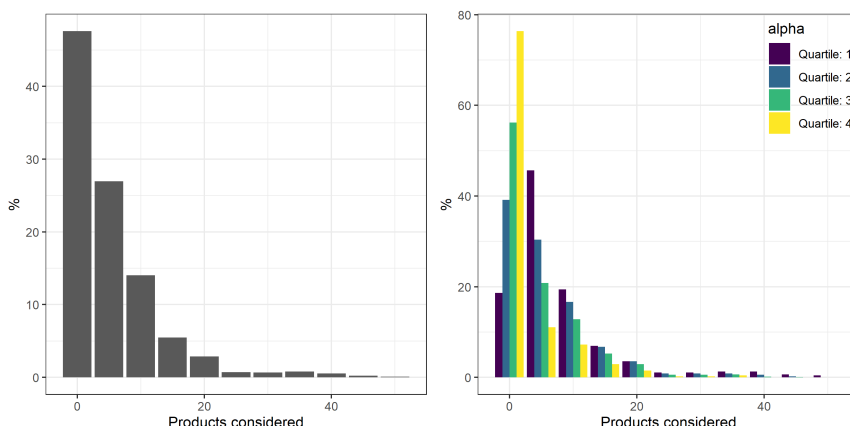
the negative correlation is more plausible for the Home & Kitchen product markets studied here. Household income, which is not observed, is likely to be a driver of both dimensions, with higher-income individuals being less price sensitive and having a higher cost of time (i.e., search cost). It is worth noting that while the estimated search cost distribution extends into negative search costs, the model simply interprets the negative search costs as zero search costs (i.e., there are no consumers that enjoy searching).

Figure 11: Estimated Consumer Heterogeneity



Next, I examine what the model implies about search activity on the platform (with consumers that choose the outside option or the “other platform” counted as having considered “zero” products). The model predicts around 25% of individuals (or around half conditional on choosing the platform) examine only the first 5 products, and that continues to drop off when moving down the search results (Figure 12). This appears sensible for the search effort that would be expended for the range of Home & Kitchen goods considered. Splitting by consumer price sensitivity also illustrates the selection into the platform that occurs, with on-platform consumers being comparatively less price sensitive.

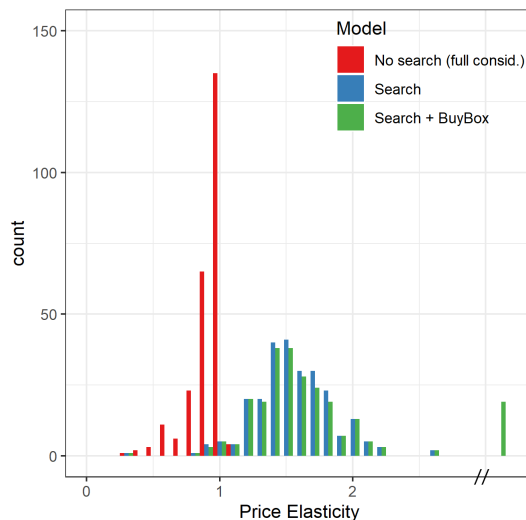
Figure 12: Implied Search Depth



This figure on the left shows what proportion of consumers search to what depth of the search results, as indicated by the number of products they considered. The figure on the right shows the same information separately for each quartile of the price sensitivity distribution. Note that the leftmost column is for “0” products considered, these are the consumers who choose the “other platform”.

Stepping back, a natural motive for estimating a model with search is so that effects attributable to consumer search costs are not erroneously attributed to consumer price sensitivity. To put it another way, we want to obtain a more accurate measure of price elasticities by incorporating search. This is true for general search models, but the current model has an added dimension of the importance of the BuyBox grouping for determining the price elasticity for certain products (products where there is fierce competition between sellers of that same product). This can be highlighted by (1) estimating the model without accounting for search, (2) accounting for search but ignoring the BuyBox and (3) accounting for search and including the BuyBox (Figure 13). Not surprisingly, a model without search mistakes a lack of reaction to the prices of products not frequently searched as price insensitivity (and unreasonable price markups), which a model with search corrects. Additionally, taking into account the BuyBox grouping reveals that price elasticities are markedly higher for the products affected by intense BuyBox competition.

Figure 13: Price Elasticity from a Dollar Increase



6 Market Power and Antitrust Policy

In this section, I (i) quantify the market power the product arrangement grants to Amazon and TPSs, and (ii) examine how possible antitrust action impacts consumer search and choice, and firm profits. I do so through two sets of counterfactual analysis. One of the key contributions of the model is that I can calculate counterfactual market outcomes under alternative product arrangements.²⁷ I can do this because the tree-form of the product arrangement is an input to the model. Consumers in the model re-optimize their search process having rational expectations of the new arrangement, and firms re-optimize their prices taking into account consumers' new search behavior. Importantly, the consumers make new search decisions holding fixed their preferences and search cost (but will incur different total costs from searching).

Some caveats and limitations are important to note: the counterfactuals only cover the products I have modeled; there is no modeling or re-optimization of advertising behavior; there is no firm entry or exit; the platform does not re-optimize its commission rate; and the characteristics of the outside options are held fixed.²⁸

²⁷Reduced-form approaches for consideration set probabilities could in principle approximate a structural model by having rich individual demographic covariates that are also then interacted with both the product's own and rival products' characteristics. This would be necessary since including only position as a variable would lead the accompanying coefficient to absorb the effects of both the consumer's search cost and their optimal search process. However, the interactions and polynomials required to approximate an optimal search process would likely be burdensome for existing datasets. Nevertheless, reduced-form models have the advantage of being comparatively more agnostic about the search process, but here I need to take a stance on how search functions, as understanding how the search process changes under counterfactuals is key.

²⁸Modeling re-optimization of commission rates requires a plausible objective function for the platform. However, the platform currently sets a uniform commission rate for the entire Home & Kitchen category, indicate it finds it optimal to not set product specific commissions. Further, the commission rate remains fixed for multiple years, leading to little useful variation for recovering the parameters of its objective function.

The first group of counterfactuals poses product rearrangements within the existing layout of the platform and decomposes the market power attributable to the status quo arrangement. The second group of counterfactuals, due to their antitrust nature, examine broader changes that include the addition/removal of products and modifications to the layout that represent potential antitrust actions.

I provide a summary of the results here (Table 5) before delving deeper into key counterfactuals of interest in the subsections below.

Table 5: Summary of Counterfactuals

	Consumer Welfare	Amazon Sales Profits	TPS Sales Profits
<i>Market Power</i>			
Neutral Arrangement	-8%	-42%	+156%
Removing Ads	+0%	-4%	+23%
Removing Editorials	-3%	-14%	+58%
<i>Antitrust</i>			
Ban Vertical Operations	-32%	-100%	+199%
Platform Split	+3%	-25%	+382%

For the class of market power counterfactuals, the key results is that the status quo product arrangement confers significant market power to Amazon’s products. Randomizing the search results through the impartial gatekeeper, removing ad listings and removing editorial listings all result in a shift of profits from Amazon to the TPSs. This reflects how, under the status quo, all of these features place Amazon’s products in better positions than those of the TPSs. However, it is important to note that the status quo arrangement is more beneficial to consumers than the proposed counterfactuals, with consumer welfare generally harmed in the counterfactuals.²⁹ I provide more details of the “Neutral Arrangement” counterfactual in the subsection below.

For the class of antitrust counterfactuals, there is an increase in TPS profits that reflects the intended effect of these antitrust policies to reduce the market power of Amazon. However, my results suggest that certain antitrust policies could lead to material consumer welfare losses. I explore the two antitrust counterfactuals in further detail below.

²⁹The only exception to this is “Removing Ads”, which leads to null effects on consumer welfare. This partly reflects the minor changes that this action represents to the listing given the overlap in products in the ads and organic listings. Of course this not innocuous for ad revenue and the ability of new products to promote themselves, two aspects of the platform I do not capture.

6.1 Impartial Gatekeeper

In markets where there are more than hundreds of slightly differentiated products, the platform faces a unique problem in deciding what products to show to consumers that dislike search. By deciding the order of products in the search results, Amazon inevitably chooses winners and losers (i.e., conferring market power on some and taking it away from others), and there have been concerns that it may do so “unfairly”. It is a complex problem to disentangle whether the current arrangement favors products sold by the platform owner (“self-preferencing”), or if the platform owner simply chooses to sell the products that are favored by the search algorithm for some other reason (e.g., because it is more desirable to consumers). In this counterfactual, I shed light on this by answering a simpler question: What are the effects of moving to a neutral arrangement that gives equal prominence (in expectation) to products? The neutrality considered is conditional on being one of the products included in the estimation. In effect, I give products that are already popular with consumers an equal playing field with other popular products. This means that low-quality products that inevitably exist on a platform with free entry are not included in the exercise.³⁰

It is informative to step through the results: first where consumers re-optimize search and purchase, but prices are fixed; and then when firm re-optimized prices taking into account consumers’ re-optimization. The counterfactual results for a full range of metrics is provided in [Figure 14](#).

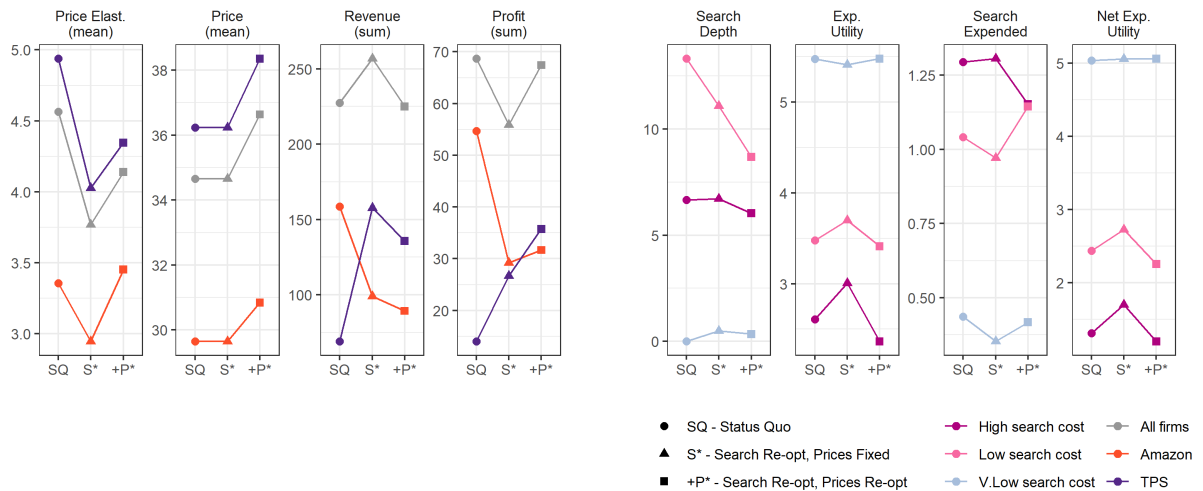
In holding prices fixed, the question I ask is: For the products as observed at their current prices, would consumers benefit from having products that were previously further down in the search results brought up in the search results? Are desirable products being placed out of reach of consumers by the platform? I find that, yes, consumers are in fact better off and would prefer the neutral arrangement, with net expected utility (expected utility less the utility cost of search) increasing. Breaking this down, both low and high search cost consumers obtain better consideration sets (higher expected utility). High search cost consumers do not change their search behavior much (incurring similar search costs), while low search cost consumers search slightly less, being satisfied with a smaller consideration set. On the supply side, TPSs see significant gains in profits, since it is mainly TPS products that now have a higher probability of obtaining a better position. Mirroring this, Amazon’s seller profits fall due to worse positions, and although the platform’s revenue (on which the commissions of the Amazon platform are taken) are higher, Amazon’s sum of platform commission and sales profits is lower.

³⁰I cannot rule out the possibility that the search result algorithm severely disadvantages very high-quality products such that I would not observe their existence in my data. However, this does not seem likely given the incentives in the model I have envisioned—the platform ultimately obtains a sizable commission for any sales and competes with another platform for consumers.

However, including both consumer re-optimization and firm price re-optimization changes many of the above conclusions. Consumers across the search cost distribution end up slightly worse off. This is driven by an overall increase in price due to two forces. First, TPS products take advantage of their increased market power from their better positions, and their increase in prices outweighs the decrease in Amazon prices. Second, since I estimate a mixed-logit demand system, competition between close substitutes in characteristics space is also a factor. Under the status quo, the prominent products are collectively closer substitutes. By moving to the neutral arrangement, the expected set of equally prominent products have greater dispersion in characteristics, and this reduces substitutability pricing pressure.³¹ While both TPS profits and Amazon sellers profits are higher from when prices were fixed, relative to the status quo Amazon profits are lower while TPS profits are higher. Platform revenues fall slightly from the status quo.

In summary, naive observation could conclude that the platform is making product consumers desire less accessible. However, neutralising the current arrangement could be harmful to consumers as some firms will increase prices to take advantage of their increased market power.

Figure 14: Impartial Gatekeeper - Results



Each panel displays the results for a different metric. Within each panel, for each line moving left to right, I show the metric under the status quo (SQ; circle), then where that metric moves to when implementing the counterfactual allowing consumers to re-optimize search but holding prices fixed (S*; triangle), and finally where the metric moves to when allowing both consumers to re-optimize search and firms to re-optimize prices (+P*; square). Within each panel, the different lines represent a different subset of the consumers or firms corresponding to the provided legend. Note that “V.Low search cost” consumers are the around 45% of consumers who under the status quo chose the “other platform”. The primary consumers of interest are the “High search cost” and “Low search cost” consumers that chose the platform under the status quo.

6.2 Vertical Operations Ban

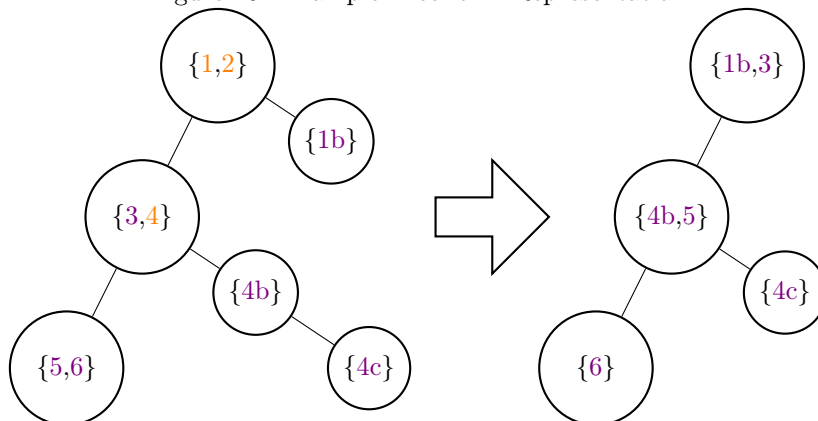
In the “Investigation of Competition in Digital Markets Majority Staff Report and Recommendations” from the US congressional subcommittee investigating the market power of Amazon and

³¹Additionally, almost half of the effects are realized when randomizing just the top 4 products’ positions, reflecting the importance of the top positions in the search results.

other platforms, the report recommended “structural separation.” The report noted that this would “...prohibit a dominant intermediary from operating in markets that place the intermediary in competition with the firms dependent on its infrastructure.” The committee was not specific as to along what lines separation should occur. Here, I consider a natural line that has also been proposed by other prominent policymakers, which is to prevent Amazon from participating as a seller on the platform it owns. This has been noted in popular media as

Calculating this counterfactual outcome is not as straightforward as simply removing Amazon products from the demand model. For the vast majority of products on Amazon, there are sellers “waiting in the wings” to sell even if policymakers were to remove Amazon as a seller. The exception are products where Amazon is the sole seller (e.g., Amazon brands), where removing these would instead free up space in the search results. This shifting and rearrangement of products uniquely requires my model, which treats product arrangement as an input, to calculate this change. A stylized example of the change in product arrangement is given in [Figure 15](#).

Figure 15: Example Tree-form Representation



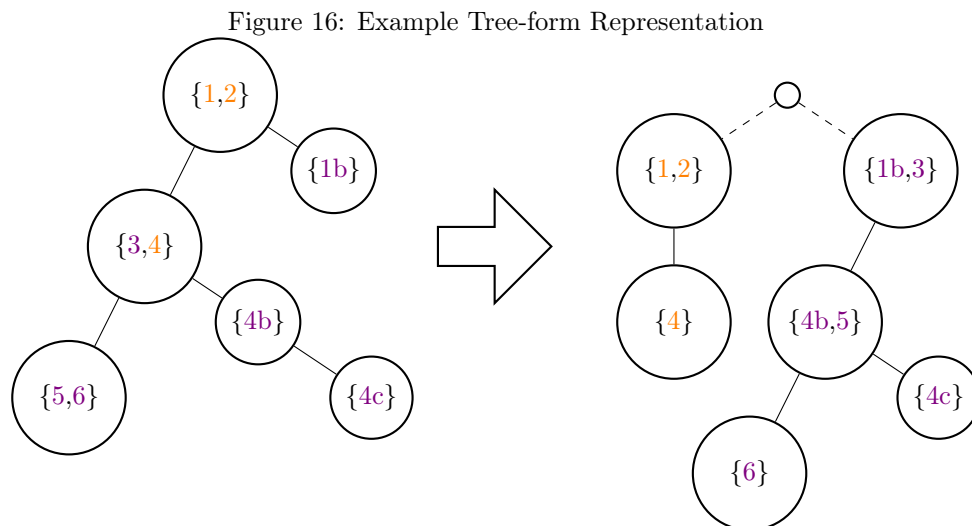
This diagram provides a simple illustration of how vertical divestiture is implemented into the model through a change in the arrangement of products. Amazon products are shown in orange, while TPS products are shown in purple. Observe that there are instances where Amazon is the seller in the BuyBox and in the search results (in the larger nodes), but there are TPSs selling the same product (the same number but with a letter subscript) in the BuyBox grouping side nodes. When I remove the Amazon products, I push the TPS products up into the main node to mimic the application of the BuyBox rules. Any product which has no replacement creates a space in the search results, and I shift the search results up to fill the gap.

Preventing Amazon from selling on its own platform is designed to address concerns that Amazon competes on an unequal basis with the millions of small to medium-sized businesses on its platform (TPSs). Implementing the prohibition, I predict TPS profits would increase substantially by around 190% as TPS sellers fill the space left by Amazon. However, there is a sizeable decrease in consumer welfare of around 30%. Platform revenue falls, as the platform overall has become slightly less valuable and some consumers substitute to the other platform. Prices drift higher as the sellers that replace Amazon have comparatively higher marginal costs of supplying the product. This particular antitrust action achieves its aim of improving TPS outcomes, though this

does come at the cost of consumer welfare.

6.3 Splitting the Platform

In this counterfactual, I consider a remedy designed to address the concerns of market power difference between Amazon and TPSs, without barring Amazon from participating on its own platform. I propose to split the platform into two sides: an Amazon side; and a TPS side. Consumers would have to choose between the two sides before proceeding with their search, a choice nested under the choice of the whole Amazon platform.³² This is akin to allowing consumers to select a filter to small business products or filter to Amazon products option in the search results. A stylized example of the change in product arrangement is given in Figure 16.



This diagram provides a simple illustration of how splitting the platform is represented by a change in the layout of the tree. Amazon products are shown in orange, while TPS products are shown in purple. When I split the platform, I separate the two sets of products, reapply the BuyBox rule and shift the search results accordingly.

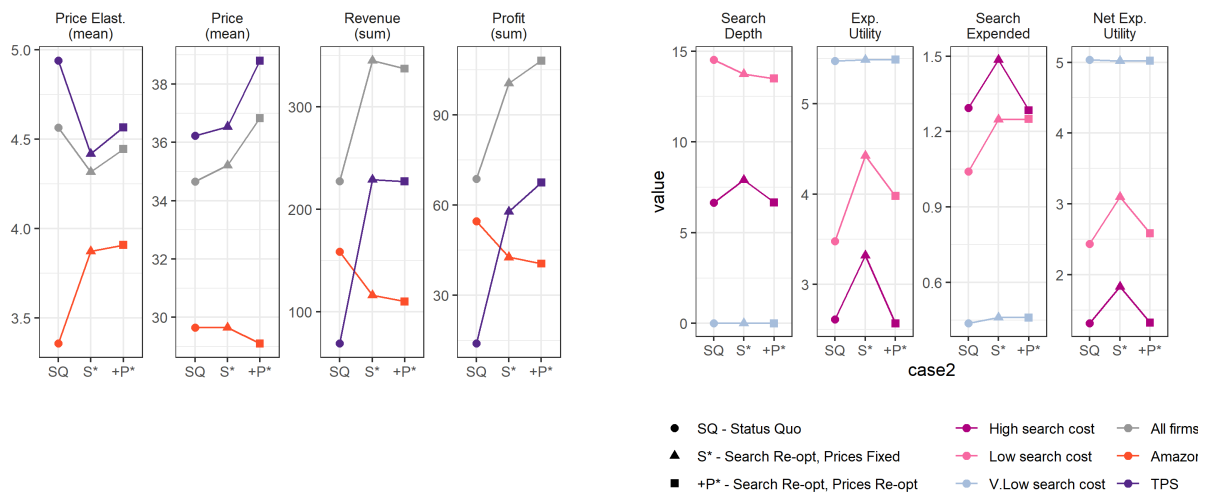
This counterfactual provides consumers with a choice between an Amazon side with a moderate number of “core” products (e.g., Amazon brand and common brands) that are generally popular, and a TPS side with effectively all of the same products as on the Amazon side, albeit at slightly higher prices, plus more fringe products that are generally less popular. The resulting equilibrium is characterized by high search cost individuals preferring the Amazon side, where there are fewer “core” products, while lower search cost consumers prefer and can benefit from the greater variety of the TPS side of the platform.

Consumers across the distribution are actually slightly better off, as the splitting of the platform provides an opportunity for consumers to self-select to the side that provides a consideration set more closely aligned with their preferences and search cost. In short, there are gains from sorting.

³²I consider the case where consumers choose one side and are locked into that side. It is possible to consider alternatives, for example where the other side can be chosen after searching one side fully.

On the supply side, Amazon prices actually fall slightly, as it attempts to attract more consumers to its side of the market, while TPS prices predictably drift higher with less direct pricing pressure from Amazon. TPS profits increase as well, since TPS are given the opportunity to sell products that normally are otherwise dominated by Amazon as a seller. Platform revenues also increase, as the further splitting of the platform allows the Amazon side to increase its appeal to high search cost, high price sensitivity consumers. Splitting the platform appears to be a viable way of addressing concerns about Amazon and TPS competition, potentially without incurring any consumer welfare loss associated with other antitrust action.

Figure 17: Splitting the Platform - Results



Each panel displays the results for a different metric. Within each panel, for each line moving left to right, I show the metric under the status quo (SQ; circle), then where that metric moves to when implementing the counterfactual allowing consumers to re-optimize search but holding prices fixed (S*; triangle), and finally where the metric moves to when allowing both consumers to re-optimize search and firms to re-optimize prices (+P*; square). Within each panel, the different lines represent a different subset of the consumers or firms corresponding to the provided legend. Note that “V.Low search cost” consumers are the around 45% of consumers who under the status quo chose the “other platform”. The primary consumers of interest are the “High search cost” and “Low search cost” consumers that chose the platform under the status quo.

7 Conclusion

In this paper, I show how online retail platforms exert market power on small businesses (i.e., third-party sellers; TPSs) by influencing the consumer search process. I build a model of consumers searching over the arrangement of products and firm pricing in response. This allows me to quantify and formalize how platform search design generates “gatekeeper” market power. The model takes as an input the product arrangement in tree-form to model what consideration sets can be formed by consumers that search optimally. This in turn eliminates impossible consideration sets and alleviates the typically large combinatorial problem of consideration set probabilities. I extend the set of demand estimation techniques using aggregate market share by providing a way to recover

consumer search costs and derive consideration set probabilities that are structural.

Data shows that products sold by Amazon are better positioned than products sold by TPSs, but this does not necessarily reflect “self-preferencing”. Reduced-form results demonstrate the importance of position in the search results for consumer demand, but they also demonstrate the need for a structural model of search to disentangle the market power generated by search design.

To decompose the market power granted by the status quo arrangement, I use the model to see how the outcomes of Amazon, TPSs and consumers change under alternative arrangements of products. Under a number of natural alternative arrangements, profits shift from Amazon to TPSs, reflecting the removal of market power Amazon enjoys due to their favorable position in the arrangement of products. If prices were fixed, consumers would in fact prefer a neutral arrangement that conditionally randomizes search results, naively suggesting that products valuable to consumers are being held out of reach. However, once firms take into account their new positions and the change in market power, prices rise and consumers are harmed. Overall, this suggests that Amazon’s incentives and consumer preferences are aligned.

To contribute to the ongoing antitrust discussions, I use the model to simulate proposed antitrust actions. I show that banning Amazon from being a seller is likely to lead to consumer welfare loss, even if it achieves the aim of improving TPS outcomes. Consequently, I propose an alternate solution, splitting the platform and allowing consumers to choose a side. This leads to sorting within the platform, with each side catering to consumers of different search costs and tastes. Under this scenario, consumer welfare is not harmed, Amazon continues to sell and the market power imbalance between Amazon and TPSs is alleviated.

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A Solution to Optimal Search

This appendix provides additional details about the solution to optimal search. The full information assumption is maintained, before being extended to rational expectations below. There are a number of features of the search problem that make the solution relatively simple: there is no time discounting; costless recall simplifies the path taken over the tree; products are only added to (not removed from) the consideration set; and consumers' expected utility only increases with actions (since search costs are sunk). Note that while the tree-form is a compact way of representing the arrangement of products, we could also expand the traversal decisions into an extensive-form single agent decision tree. As an extensive-form decision tree, the search problem reduces simply to which ultimate consideration set a consumer wants to form and the costs of getting there. When considering a mass of consumer search costs with full support, we can first consider the optimal path of an individual with no search cost and relegate the stopping decision to the problem of finding the indifferent individuals that would stop searching at some point. After all, conditional on taste heterogeneity, a mass of consumers with different search costs only differ from each other based on the depth of their search.

Recall that consumers make their traversal decisions sequentially and search costs are sunk. At any stage of search consumer i with current consideration set \mathcal{C}_i will add products to their consideration set to form a new consideration set $\mathcal{C}'_i \supset \mathcal{C}_i$, incurring traversal cost $t(\mathcal{C}_i, \mathcal{C}'_i) s_i$ if:

$$E_\epsilon \left[\max_j \{\delta_{ij} + \epsilon_{ij}\}_{j \in \mathcal{C}'_i} \right] - E_\epsilon \left[\max_j \{\delta_{ij} + \epsilon_{ij}\}_{j \in \mathcal{C}_i} \right] \geq t(\mathcal{C}_i, \mathcal{C}'_i) s_i$$

or $EU(\mathcal{C}'_i) - EU(\mathcal{C}_i) \geq t(\mathcal{C}_i, \mathcal{C}'_i) s_i$.

It is much simpler to solve the search problem for the entire distribution of individuals and, in particular, by focusing on the indifferent consumers as we move across the search cost distribution. First, note that for individuals with $s_i \leq 0$, they search fully through the entire tree and obtain full consideration. As we move up the search cost distribution, we only need to consider whether the last search action taken (i.e. any possible end node) would in fact become sub-optimal to take. Note that for two consumers who differ slightly in search costs, s_i and $s_i + \epsilon$, if $EU(\mathcal{C}'_i) - EU(\mathcal{C}_i) \geq t(\mathcal{C}_i, \mathcal{C}'_i)(s_i + \epsilon)$ then $EU(\mathcal{C}'_i) - EU(\mathcal{C}_i) \geq t(\mathcal{C}_i, \mathcal{C}'_i) s_i$, for all possible consideration sets \mathcal{C}'_i . This is why consumers with different search cost only differ in the depth of their search. Additionally, note that for any pair of consideration sets $\mathcal{C}''_i \supset \mathcal{C}'_i$, optimality of choice and i.i.d. taste shocks ensures that $EU(\mathcal{C}''_i) > EU(\mathcal{C}'_i)$. The fact that the benefits of searching are always increasing is useful as the sequential decision process will not result in "mistakes". Taken together, the above

means that as we move up the search cost distribution, we will find the indifferent individual who would not search the last optimal node. This indifferent individual is given by the first \mathcal{C}'_i in all possible consideration sets where $\text{EU}(\mathcal{C}'_i) - \text{EU}(\mathcal{C}_i) = t(\mathcal{C}_i, \mathcal{C}'_i) s_i$. Further, observe that we can split $t(\mathcal{C}_i, \mathcal{C}'_i)$ to obtain $\text{EU}(\mathcal{C}'_i) - t(\{0\}, \mathcal{C}'_i) s_i = \text{EU}(\mathcal{C}_i) - t(\{0\}, \mathcal{C}_i) s_i$. This is the intersection of two Ex-ante Expected Utility functions. Finally, note that a sub-optimal next step is one where a consumer holding \mathcal{C}_i has the choice of more than one choice, say \mathcal{C}'_i and \mathcal{C}''_i , where the two ExEU functions (in the space of utility and search costs) are parallel and the sub-optimal choice lies strictly below that of the optimal choice. Thus, solving for the upper envelope of ExEU functions is equivalent to solving for the optimal search path for the distribution of consumers.

To extend this to rational expectations is straightforward. Importantly, I require the expectations to be drawn from the distribution with replacement. This means that consumers will not change their expectations about the products and utility available at other nodes based on information realized in the nodes already traversed. This would be problematic if we want to allow consumers to have incorrect beliefs about products, which are then corrected as search actions are taken. However, here I study products where this is unlikely to be important. Note that the optimal search path remains unchanged. While realisation of the actual utilities in explored nodes lead to changes to the utility on hand and therefore the utility achievable from traversal, the ranking of the available traversal nodes do not change. A similar logic is noted in [Weitzman \(1979\)](#) and other papers dealing with sequential actions. That is, the optimal path remains the same, only the cut-off changes—the indifferent individual shifts up or down in their search costs depending on whether the realized utility is higher or lower.

B Data Collection Details

This appendix provides additional details about the collection of the data. Broadly speaking, the data collection process is designed to mimic an actual consumer search process. The scraper navigates through the website just as a consumer would, recording information shown on the webpages as it traverses.

Search begins when the scraper searches for a particular category of product using a keyword. Data on search keywords, typically collected for search engine optimization and advertising pricing analytics, are used to determine the keywords that consumers use when they search for the product categories studied. To ensure a representative sample, the scrapers use the keywords that comprise at least 80% of the volume of the top 20 keywords used. The scrapers collect information on the first 3 pages of search results, which amounts to around 100 products, but varies depending on

the product category. For each product shown in the search results, the scraper navigates into the product page, as well as the page listing non-BuyBox sellers, and records the relevant information. The scraping process is repeated throughout the week, and results in around 30 observations of search results each week for each product category.

The scrapers utilize a range of IP addresses that are dispersed throughout the US. No significant differences in collected data were found based on the geography of the IP. The scrapers obtain search results that are not personalized or conditional on prior purchase history. The product categories studied are durables that are infrequently purchased by households and the platform may not have strong priors on the preferences of the households with respects to these products. Past behavior of preferences in other product categories may not be informative of preferences in these categories (e.g., a price sensitive electronics consumer may not necessarily be a price sensitive kitchen appliance consumer).

The data collection focuses only on ‘New’ condition goods and I model the consumers as ignoring any used goods, which only appear in the non-BuyBox pages of the site for these mature product categories.

B.1 List of Markets

The categories or markets are existing categories defined by Amazon contained within the broader Home & Kitchen category. I exclude markets that are not end-points, for example coffee machines is a broader category containing many sub-categories of specific types of coffee machines. Similarly, I exclude markets that are not well defined for the search process, specifically where the search term for the product returns search results with less than 50% of products being in that category. For example, a search for coffee machine returns a wide range of espresso, drip and grinder machines that belong to separate categories of products.

Table 6: List of Markets

air fryer	hair straightener	rice cooker
air purifier	hand mixer	robot vacuum
back massager	handheld vacuum	salad spinner
bathroom scale	humidifier	shaver
blood pressure monitor	ice cream maker	slow cooker
bread machine	immersion blender	sous vide
chocolate fountain	infrared thermometer	space heater
crepe maker	iron	stand mixer
dehumidifier	jigger	steamer
digital picture frame	kitchen scale	toaster
electric can opener	laser hair removal	toaster oven
electric griddle	light therapy lamp	towel warmer
electric kettle	measuring spoons	tower fan
electric pressure cooker	meat grinder	vacuum sealer
electric soap dispenser	milk frother	waffle maker
electric toothbrush	oil diffuser	water flosser
food processor	oil sprayer	white noise machine
foot massager	pasta maker	
hair curler	pedal exerciser	
hair dryer	pulse oximeter	

C Estimation of Market Share

This section describes the estimation of the sales of each product per week that forms the market shares necessary for demand estimation.

To calculate sales for each product, I estimate the relationship between sales ranking (i.e. the order of sales per product within a category reported by Amazon), which is fully observed, and number of sales, which is partially observed through inventory level changes for around one-third of all products in my sample. Inventory data is observed by the scrapers during the process of navigating the products. When adding a large number (i.e., 999) of a particular product to the shopping cart, for around one-third of products, the platform displays the remaining stock level for that product at that point in time. In the remaining two-thirds of products, information about inventory level is uninformative because stock levels exceed the maximum purchasable amount (e.g. there are more than 999 remaining) or there is a maximum purchase limit. The approach of relating sales ranking and sales was introduced by [Chevalier and Goolsbee \(2003\)](#), though here I follow a predictive approach to estimation and use a large sample of sales data. [He and Hollenbeck \(2020\)](#) also uses the same method to obtain inventory data and estimate market shares that spans a broader set of markets than examined here.

Estimation of market share proceeds in two broad steps. First, I transform the limited observations of inventory over time into estimates of sales. Second, I estimate the relationship between the estimates of sales and the fully observed sale rank data to back out estimated sales for all

products.

To obtain sales I calculate how inventory decreases over repeated observations. The time in which observations occur are stochastic and so I need to take into account the period of time elapsed between observations and their time of day. Sales are likely to be higher during the US day than during the US post-midnight and early morning.

Formally, consider a setup of discrete time $t \in T$ of sufficiently small time units (e.g., seconds). The remaining inventory level of firm i selling product j is given by:

$$\text{inventory}_{ijt} = \text{inventory}_{ijt-1} - \text{purchases}_{ijt} + \text{returns}_{ijt} + \text{restocks}_{ijt} \quad ,$$

where inventory this moment is the inventory one t ago, less any purchases made this t , adding back returns/refunds of purchases, and adding restocking of inventory. The change in stock level from $t - 1$ to t is:

$$\Delta \text{inventory}_{ijt} = - \text{purchases}_{ijt} + \text{returns}_{ijt} + \text{restocks}_{ijt} \quad .$$

Let the purchase, returns and restock flows be weakly positive and follow their own random processes (drawn from independent distributions with positive support):

$$\begin{aligned} \text{purchases}_{ijt} = \epsilon_{\text{purchases},ijt} & \geq 0 \\ \text{returns}_{ijt} = \epsilon_{\text{returns},ijt} & \geq 0 \\ \text{restocks}_{ijt} = \epsilon_{\text{restocks},ijt} & \geq 0 \end{aligned}$$

I impose the key assumptions that $\text{purchases}_{ijt} \geq \text{returns}_{ijt} \quad \forall i, j, t$ (i.e., purchases always exceed returns in any discrete time t) and $P(\text{restocks}_{ijt} > -\text{purchases}_{ijt} + \text{returns}_{ijt} | \text{restocks}_{ijt} > 0) = 1$ (i.e., restocks, when they are non-zero, are strictly larger than net purchases), but each process is otherwise uncorrelated and i.i.d across time. These assumptions imply that:

$$\Delta \text{inventory}_{ijt} = \begin{cases} -\text{purchases}_{ijt} + \text{returns}_{ijt} & \Delta \text{inventory}_{ijt} \leq 0 \\ -\text{purchases}_{ijt} + \text{returns}_{ijt} + \text{restocks}_{ijt} & \Delta \text{inventory}_{ijt} > 0 \end{cases}$$

and it follows that $\frac{T}{\mathbf{1}(\Delta \text{inventory}_{ijt} \leq 0)} \sum_{t \in T} (\Delta \text{inventory}_{ijt} \mathbf{1}(\Delta \text{inventory}_{ijt} \leq 0))$ is an unbiased estimator of sales $\sum_{t \in T} (-\text{purchases}_{ijt} + \text{returns}_{ijt})$, with consistency given as the frequency of observations increases.

The inventory measure of quantity sold only provides sales estimates for the products for which

inventory is observed. I use the relationship between Amazon’s sale rank data (available for all products) and the stock measure of quantity sold to predict the quantity for products where I do not observe inventory data. Specifically I estimate predictive regressions of the form:

$$\text{sales}_{ijt} = \alpha_m + \beta_m \log(\text{rank}_{ijt}) + \epsilon_{ijt} \quad ,$$

where the coefficients α_m and β_m are separately estimated for each market of products, which have their own corresponding ranks. The regression obtains an $R^2 = 0.67$, in line with other predictive estimates using inventory data. Different specifications involving different time scales or inclusion of lags do not appear to produce materially different results. The predominant variation used in the paper is within product variation and comparisons of the raw rank data and estimated sales data appear consistent (see [Table 2](#)).

D Rank-Ordered Logit of Search Results

This appendix models the search results positions using a rank-ordered logit framework. These results highlight the relatively small size of the relationship between the price of the product and the search results positions.

[Table 7](#) estimates the rank-ordered logit on the 777 search results list for the Waffle Makers market. I restrict attention to organic search result positions and the approximately 100 products that appear in at least 20% of the 777 search results lists. This eases the computation burden and focuses our estimated effects on the products most commonly seen by consumers in the search results.

The results show there is an estimated effect of price on position, and in the expected direction. Recall a lower position is a better position, thus negative signs should be interpreted as an correlated improvement in position. Note there is no statistically significant effect when a product switches from being sold by TPSs to Amazon (i.e., the BuyBox seller changes). All models include product-level fixed effects.

Table 7: Rank-Ordered Logit of Search Results - Waffle Makers

	(1)	(2)	(3)
Price	-0.0035* (0.002)	-0.0150*** (0.003)	-0.0183*** (0.003)
Sold by Amazon		0.0024 (0.124)	0.1812 (0.132)
Shipped by Amazon		0.3959** (0.135)	0.3168* (0.147)
Star Rating (/5)		-0.3746* (0.182) (0.014)	-1.0625*** (0.186) (0.019)
No. of Reviews		0.0000*** (0.000)	0.0000*** (0.000)
Prev. Week Sales Ranking			-0.0002*** (0.000)
Observations	52880	13612	12826
Product FEs	Y	Y	Y
Average product-level SD of position	15.39	5.74	4.53
Counterfactual effect of 10% own price decrease:			
mean position change	-0.18	-0.2	-0.22
mean % position change	-0.7	-1.9	-2.18

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For each product, I calculate the counterfactual effect of a 10% own price decrease on the predicted search result position, holding other product prices fixed. Note that a 10% price decrease is substantial in these product markets and is likely a significant share of the profit margin. Averaging the counterfactual effect across all products in the regression, the effect of a price decrease on position is minor, ranging from a 0.18 to 0.22 improvement in position. In comparison, the average standard deviation of position for a product across search results is 5 to 15 positions. Thus sellers appear to have a limited ability to influence their position by changing their own prices. Or put differently, the algorithm that generates the search results appear to respond only minorly to product price changes. In terms of heterogeneity of effect, products typically in a better position have smaller counterfactual effects.

E Weak-IV Tests for Linear Model

This appendix considers the weak instruments problem for a simple analogue of the structural model.

A classic concern with instrumental variable estimation is the possibility of weak instruments that render classic inference invalid. In the model, I motivate the exclusion restriction through the imposition of an AR(1) assumption (discussed in the body of the paper). However even if the exclusion restriction holds, the instruments may lack relevance or be weakly powered. Issues with

weak instruments are discussed by [Stock et al. \(2002\)](#).

The study of weak instruments for multiple endogeneous variables in nonlinear GMM models trails behind that in linear IV models. Thus the common tests for detecting weak instruments do not apply to my model. As an alternative, in this section I provide the common test statistics for a approximate linear “interpretation” of the nonlinear main model estimated in [Section \(4\)](#). Specifically, I consider the linear model:

$$\log(s_j) - \log(s_0) = -\alpha_1 \text{price}_{jt} - \alpha_2 \text{price}_{jt}^2 + \beta_1 \text{pos}_{jt} + \beta_2 \text{pos}_{jt}^2 + \gamma \text{price}_{jt} \times \text{pos}_{jt} + \xi_{jt} + \epsilon_{jt} \quad ,$$

where s_j is the market share for product j , s_0 is the market share for the outside option, α_1 and α_2 are the coefficients notionally capturing the heterogeneity/nonlinearity in price sensitivity, β_1 and β_2 are the coefficients notionally capturing the heterogeneity/nonlinearity in search effects, γ captures the correlation between price sensitivity and search effects and ξ_{jt} is a product-time fixed effect. Thus, the squared terms here serve as a rough analog to the heterogeneity parameters in the main model. I consider the same set of instruments detailed in [section 4.1](#) that are used in the main model. As suggested by [Stock and Yogo \(2005\)](#), I report the first stage F-stat, Cragg-Donald F-stat and the conditional F-stats. Keeping in mind that the results here for the linear model has a limited relationship to the results in the main nonlinear model, the tests indicate the null hypothesis that the instruments are weak is rejected for this linear model.

Table 8: Weak IV Test

	(1)	(2)	(3)	(4)	(5)	(6)
Treated as endogenous						
price	Y	Y				
price ²	Y		Y			
pos	Y			Y		
pos ²	Y				Y	
price × pos	Y					Y
Cragg-Donald F-stat	12.14	559.3	66.36	16.00	88.86	32.74

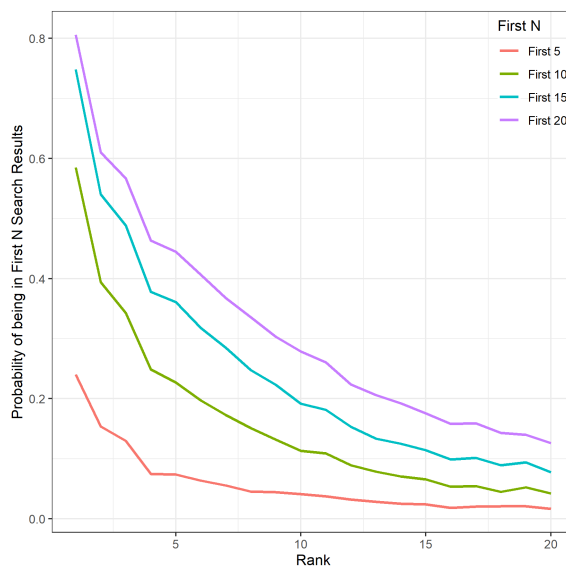
F Additional Statistics

F.1 Position and Rank

This appendix shows the likelihood of appearing in the first N positions in the search results as a function of the product’s sales rank. The considerable stochasticity is likely necessary to disperse the significant market power that would arise from more deterministic positions. This stochasticity

is also why it is important for the structural model to take in the distribution of product positions, as opposed to summary statistics (like an average position), which obfuscate the true effects of positions.

Figure 18: Probability of Appearing in First N Positions in Search Results



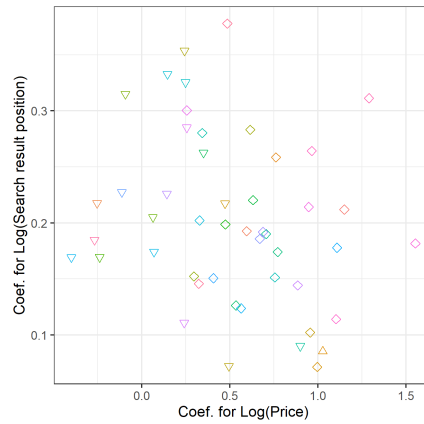
The figure above shows the relationship between a product’s Best-Seller Ranking and the probability of showing up in the search results’ first N positions. All the lines are downwards sloping, reflecting the higher likelihood of being in a better position given a better rank. It also illustrates the stochastic nature of the search results, such that even products in the top 5 Best-Seller Rankings are not always shown to consumers.

F.2 Market-level Regression

In this appendix, I explore whether there is enough variation in each of the markets to allow for structural estimation. To do so I run the following regression separately for each market, and plot the price and position coefficients for the different markets in [Figure 19](#).

$$\log(\text{Rank})_{jt} = \beta_1 \log(\text{Price})_{jt} + \beta_2 \log(\text{Position})_{jt} + \text{ProductFES} + \epsilon_{jt}$$

Figure 19: Estimated Coefficients across Markets



The diamonds indicate coefficients that are statistical significant for both $\log(\text{Price})$ and $\log(\text{Position})$. The upwards pointing triangles indicate only the $\log(\text{Price})$ coefficient is significant, while the downwards triangle indicates only the $\log(\text{Position})$ coefficient is significant. All statistical significance is for at least the 10% level.

It appears that a majority of markets have sufficient variation to establish significance for both price and position and would be good candidates for structural estimation.