CESifo WORKING PAPERS

10786
2023

Original Version: November 2023
This Version: January 2024

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 10786*

Consumer Search: What Can We Learn from Pre-Purchase Data?

Abstract

Researchers are increasingly able to observe consumers' behavior prior to a purchase, such as their navigation through a store or website and the products they consider. Such pre-purchase (or search) data can be valuable to researchers in a variety of ways: as an additional source of information to estimate consumer preferences, to understand how firms can influence the search process through marketing mix variables, and to analyze how limited information about products affects equilibrium market outcomes. We provide an overview of these three research areas with a particular emphasis on online and offline retailing.

JEL-Codes: D430, D830, L130.

Keywords: consumer search, limited information, consideration sets, retailing.

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This draft: January 24, 2024
None of the authors received external funding for this paper. All errors are our own.

1 Introduction

The marketing literature has long recognized consumers typically do not choose from all available products, but instead form consideration sets out of which they decide which product to buy (see, e.g., Howard and Sheth 1969, Gensch 1987, Hauser and Wernerfelt 1990, Roberts and Lattin 1991, Shocker et al. 1991).[1] Due to technological advancements, the consumer search process has increasingly become observable. For example, RFID tags and geo-location data enable firms and researchers to track consumers' movements in a physical retail store. In online retail, browsing data permit researchers to observe which products a consumer inspects before making a purchase. In this article, we outline how researchers can use such pre-purchase data combined with a search model framework to gain new insights into consumer and firm behavior, with a special focus on the retail sector.

The research areas we cover are informed by two empirical patterns that have been documented across a variety of different markets. First, substantially more data are available on search than on purchase behavior in many settings because some consumers search but do not make a purchase and some consumers search multiple products. For example, Ursu et al. (2023c) document 9.5 more search than purchase incidences in their apparel data, and Zhang et al. (2023) report 45 times more search than purchase incidences for shoes on a mobile app. Second, consumers typically search very few products. Previous research documents average consideration set sizes of 2.5 for savings accounts (Honka et al. 2017), 1.4 for cosmetics (Morozov et al. 2021), and 1.7 for home improvement products (Amano et al. 2022).[2]

These two patterns suggest several areas where search data can be particularly valuable to researchers and retailers. In section 3, we cover how the richness of search relative to purchase data enables better estimation of consumer preferences. These preference estimates can then be used to inform a retailer's core marketing decisions, such as pricing. For example, targeted price promotions are traditionally based on demographic variables or past purchases (see Rossi and Allenby 1993). In settings in which these variables are not available, consumer preferences estimated from pre-purchase data can form the basis for targeted marketing strategies.

In section 4, we examine how retailers can influence consumer search through marketing tools such as store design and advertising. Decisions on how to guide consumers during the search process are important because consumers search relatively little and are likely to only discover and consider products that the retailer makes salient. For example, products that are ranked higher on a search-results page of an online retailer tend to be searched and purchased more frequently (Ursu et al. 2020). We show how a search model framework can be used to predict retailer profits as well as consumer welfare under different store/ webpage design policies. A retailer could use this approach to, for example, determine the profit-maximizing shelf layout. We also discuss how

[1] We use the terms "consideration set" and "search set" interchangeably in this paper.

[2] Additional examples of consumers' typically small consideration set sizes are 2.4 for auto insurance (Honka 2014), 2.8 - 6.4 for digital cameras (Bronnenberg et al. 2016), 2.3 for online used cars (Gardete and Hunter 2020), 1.1 for new car purchases (Yavorsky et al. 2021), and 1.9 for shoes (Zhang et al. 2023).

pre-purchase data enable researchers and retailers to better understand how advertising affects consumer decisions, by analyzing the impact of advertising along the purchase funnel.

In section 5, we discuss which price levels, as well as other outcomes, arise when both consumers and retailers behave optimally. Such an analysis of equilibrium behavior allows retailers to understand how the market evolves when search costs change due to innovations that allow for easier access to information. An example of such a change is the emergence of price-comparison websites that have enabled consumers to more easily find the retailer that offers a given product for the lowest price. Because consumers tend to search relatively few products, information frictions are likely large and therefore play an important role in shaping market outcomes.

Before we turn to these three substantive research areas, we provide some general background on different types of search data that researchers typically have access to, as well as model frameworks that have been used in the literature. This content lays the foundation for the discussion of substantive research areas in the later sections of this paper, and we frequently refer back to it. We focus on the use of search data in a retailing context and differentiate between brick-and-mortar and online retailing, due to differences in available data and in relevant marketing variables. We note we do not provide an exhaustive overview of the search literature; instead, our aim is to highlight a set of broad research areas where search data are particularly useful. We refer the interested reader to Honka et al. (2019) for an overview of the search literature.

2 Search Data and Models

In this section, we discuss the types of pre-purchase data that are typically available to researchers. Then, we turn to the model frameworks that have been employed to analyze such data starting with the Weitzman (1979) sequential search model, which has become the search framework most commonly used in empirical work. We then discuss a series of extensions to the Weitzman (1979) sequential search framework and conclude the section by providing guidance on how to select an appropriate model framework as a function of the available data and the research question that one is trying to address.

2.1 Common Types of Pre-Purchase Data

Pre-purchase data can, in principle, comprise any activity that a consumer engages in to gather information about products before making a purchase. For example, a typical pre-purchase journey of a consumer on an online retail platform might consist of entering a search query, filtering by product characteristics such as price or star rating, and finally visiting the product-detail pages for some products and purchasing one of them. In the following, we discuss common types of pre-purchase data found in online retail and in brick-and-mortar retail settings.

The most commonly used type of data containing information on consumers' online pre-purchase behavior is clickstream data. The unit of observation in clickstream data is a URL of the webpage that a consumer visited, and, typically, the researcher is able to also observe the time of the visit. In other words, clickstream data allow the researcher to observe which products a consumer searched and in which sequence. Therefore, most of the existing literature on consumer search in the online context focuses on the identities and the order of searched products and ignores other steps in the process (see, e.g., Ursu 2018, Jiang et al. 2021, Morozov et al. 2021). Sometimes, researchers have access to more detailed data that also enable them to observe how consumers scroll and navigate within a given webpage. In such cases, other consumer decisions such as sorting and/or filtering of search results (see, e.g., Chen and Yao 2017, Koulayev, De los Santos and Koulayev 2017), scrolling decisions on a webpage (Korganbekova and Zuber 2023), and the search queries that consumers employ to generate search results (Padilla et al. 2019) can be modeled.

Another source of both online and offline search data is based on eye-tracking. In a physical store, eye-tracking glasses enable researchers to gather pre-purchase data (Xu et al. 2023). However, eye-tracking data gathered from consumers who wear glasses may suffer from the fact that consumers know they are being observed, thus leading to an unnatural shopping experience. In the online environment, collecting eye-movement data using a computer camera represents a less obtrusive option (Martinovici et al. 2021; Ursu et al. 2022). Similar to clickstream data, eye-tracking data permit researchers to observe the identities and sequence of products a consumer searches.[3] However, eye-tracking data have the potential for an even more granular level of observation by recording which product attributes a consumer looked at (Ursu et al. 2022) and for how long (Ursu et al. 2020).

Except for eye-tracking, data on pre-purchase behavior in brick-and-mortar retail tend to be different in nature from online data, which affects how they can be analyzed and what kind of research questions can be addressed based on such data. A first type of offline pre-purchase data is path-tracking data that permit the researcher to observe how consumers walk through a physical store based on radio-frequency identification (RFID) tags (Hui et al. 2009, Seiler and Pinna 2017, Seiler and Yao 2017) or video tracking (Jain et al. 2020). Path-tracking data contain information that is less detailed than typical online search data and do not allow the researcher to observe which specific products a consumer considers. Instead, the researcher can only track which areas of the store were visited, when they were visited, and how much time a consumer spent in front of a particular category. The latter can be seen as a measure of category-level search intensity (Seiler and Pinna 2017), but it is a cruder measure than the detailed information on product page visits typically available in online data.

One disadvantage of both RFID and video data is that they are usually restricted to one store. This disadvantage can be overcome using a different type of offline data, namely, cellphone tracking data where a consumer's geo-location is recorded based on the location of her phone. These data enable researchers to track consumers across retail outlets. However, this type of data is usually not precise enough to record consumer movements within a store. Yavorsky et al. (2021)

[3] In the case of eye-tracking data, one needs to make an assumption about what duration of eye fixation on a product constitutes a consumer considering a product. The industry standard is that an eye fixation is defined as a period of 200–400 milliseconds during which the eye is relatively fixed on an area. In online settings, the click decision more cleanly identifies when a product was searched.

use geo-location data to study consumers' shopping process for new cars. The authors use the cellphone location to determine which dealerships consumers visit. Because search is modeled at the dealership level, the data in Yavorsky et al. (2021) are akin to online search data in the sense that they permit the researchers to observe the identities and sequence of visited dealerships.

2.2 The Weitzman (1979) Sequential Search Model

Weitzman (1979) proposes a solution to the sequential search model for differentiated products that has emerged as the workhorse model for empirical work using consumer search data. Although we do not exclusively focus on studies using this particular framework, it is the most common model of search behavior, and many alternative models can be seen as extensions or modifications to the Weitzman (1979) framework. In this section, we describe the mechanics of the model at a relatively high level to provide the necessary background needed for the applications we discuss in the following sections. We refer the interested reader to the more detailed technical overview of the sequential search model in Ursu et al. (2023a).

Similar to the well-established discrete-choice modeling approach based on purchase data (see Dubé 2019 for an overview), we assume consumer i receives utility u_{ij} from purchasing product j:

$$u_{ij} \quad = \quad \delta_{ij} + \varepsilon_{ij} \ . \tag{1}$$

We let δ_{ij} denote the part of utility that is known by the consumer prior to search. Consumers also know the distribution of ε_{ij} prior to search and need to incur a search cost c_{ij} to learn its realization for a specific product. Consumers search products sequentially until they decide to stop searching and purchase one of the searched products or choose the outside option of not purchasing. Often, ε_{ij} is thought of as a "match value" that reflects an idiosyncratic taste shock that consumers learn after getting more detailed information about a product. In general, the unknown component ε_{ij} can also reflect product characteristics such as price (Honka 2014) or combinations of characteristics (Yao et al. 2017; Compiani et al. 2023).

If the post-search utility component ε_{ij} is independently distributed across products for a given consumer, the payoff from searching a specific product does not depend on which other products were searched before. Weitzman (1979) shows that, under this assumption, the optimal search process can be summarized by a simple set of rules that depend on the so-called reservation value (or reservation utility) z_{ij} that summarizes the value of searching a particular product. A product's reservation value is equal to the value of the current utility that would make a consumer indifferent between searching product j or not searching it. Under the assumptions laid out above, the reservation utility is given by an additively separable expression that depends on search costs and pre-search utility:

$$z_{ij} = \delta_{ij} + g(c_{ij}), \tag{2}$$

where $g(c_{ij})$ is a known function that monotonically decreases in search cost c_{ij} and only depends on search costs and the distribution of the post-search component ε_{ij}.[4]

The optimal search sequence consists of a consumer searching products in decreasing order of their reservation utilities ("search rule") until the maximum realized utility among the searched products exceeds the maximum reservation utility among the unsearched products ("stopping rule"). After stopping to search, the consumer chooses the highest-utility option from the searched products, including the outside option of not purchasing ("purchase rule"). These three rules describe optimal consumer search and purchase behavior and are often called the "Weitzman rules." Importantly, the chosen option might not coincide with the utility-maximizing product in the entire assortment, because the consumer does not learn the full utility of all options.

Utility and search costs are usually parameterized in a way that resembles standard perfect-information choice models:

$$\begin{aligned} \delta_{ij} &= \boldsymbol{X}_j' \boldsymbol{\beta}_i - \alpha_i p_j + \mu_{ij} \\ c_{ij} &= \boldsymbol{Z}_j' \boldsymbol{\gamma}_i, \end{aligned}$$

where p_j denotes price and $\boldsymbol{X}_j$ and $\boldsymbol{Z}_j$ denote vectors of product characteristics that enter preferences and/or search costs. Both sets of variables can include product fixed effects, physical product characteristics, and variables that capture saliency, such as product ranking on a webpage or advertising.

A natural parameterization consists of including physical-product characteristics as part of preferences, whereas variables that do not procure utility but affect the visibility and salience of a product are included in the set of variables that shift search costs. Including variables as part of both search costs and utility and testing whether a given variable affects search costs and/or preferences is also possible (see Ursu et al. 2023a). Intuitively, a variable that lowers search costs will lead to the product being searched more often and earlier, whereas a variable that increases utility will lead to higher conversion conditional on search.[5]

Two properties of the search model are particularly important for the research areas we cover later in the paper. First, the order of search, when search stopped, and the purchase decision are informative about preferences. Therefore, search data provide additional information about consumer preferences beyond solely purchase data, which are used in traditional demand-estimation approaches. Moreover, as we discussed in the introduction, search data are often much more abundant than purchase data. Therefore, search data are likely a valuable source of information to learn about consumer preferences. In section 3, we discuss how researchers can use search data to better understand preferences.

Second, combining search data with a model of consumer search behavior enables the researcher to model the impact of variables that shift search costs by making products more salient. Many

[4] The function ranges from negative infinity (if search costs go to infinity) to infinity (if search costs are zero). See Kim et al. (2010) for an example of the expression for $g(c_{ij})$ when ε_{ij} is normally distributed.

[5] See Ursu et al. (2023a) for a formal argument regarding the separate identification of preferences and search costs.

marketing decisions, such as product rankings on a webpage or shelf placement in a physical store, are best thought of as search-cost shifters, and a search framework therefore provides a natural lens to study the impact of these marketing activities. In section 4, we discuss how firms can influence consumers' search decisions and how we can use data to learn about the impact of marketing on search.

2.3 Beyond the Weitzman (1979) Search Model

The Weitzman (1979) search model allows the researcher to model the sequence of searches and the identities of the considered products. However, other parts of the search process, such as the usage of sorting or filtering tools or the search queries a consumer enters, cannot be easily modeled using the standard Weitzman framework. As we discussed in section 2.1, researchers sometimes have access to additional pre-purchase behaviors, but only a small number of papers have incorporated information beyond the sequence of searched products. We discuss some of these papers in the following.

Chen and Yao (2017) amend the Weitzman (1979) model to incorporate consumers' decisions to refine search results. The authors estimate a sequential search model in which sorting and filtering decisions change the distribution of characteristics in the list of search results.[6] Intuitively, a consumer who chooses to sort products by price will tend to be more price sensitive, and hence, the sorting decision provides valuable information about preference parameters. Koulayev (2014), De los Santos and Koulayev (2017), and Gu and Wang (2022) similarly incorporate sorting and filtering into a sequential search model.

Using a version of the search and discovery model developed by Greminger (2021), Zhang et al. (2023) allow consumers to take different search routes (e.g., navigating through the main category page or the sales page of the website) to reach the same product. Similar to the consumer decision to refine search results, the choice of a search route also provides information about consumer preferences. Moreover, the ways in which consumers are allowed to navigate a webpage are set by companies and constitute a major decision through which firms can impact consumers' search and purchase behavior. We return to this issue in section 4.2.

Search queries can also contain information about preferences, because consumers might mention specific brands or product attributes that they are looking for in a category. Due to their high-dimensional and open-ended nature, search queries are inherently more difficult to analyze than the binary decision of whether to search a product or to use sorting and filtering options. The closest work dealing with search queries is that by Liu and Toubia (2018), Liu and Toubia (2020), and Liu et al. (2021), who analyze consumers' content preferences based on their search queries. All three papers analyze search queries in isolation, do not combine search-query data with purchase data or other information about consumer search behavior, and do not use a search

[6] The paper also assumes search costs are higher for products with higher ranks (i.e., products that are displayed further down on the results page). Therefore, re-sorting products with desirable characteristics toward the top will tend to lower search costs.

framework. Padilla et al. (2019) is the only paper we are aware of that combines search queries and search data to analyze the customer's journey. The authors do not estimate a search model, but rather develop a statistical model of the consumer's purchase journey that can be used to predict consumer choices based on their pre-purchase behavior.

Finally, several papers incorporate additional information about the products a consumer searched. Ursu et al. (2020) amend the sequential search model by incorporating the decision of how long to search a product in the sequential search model. Equipped with eye-tracking, Ursu et al. (2022) observe not only which products a consumer looked at, but also which product attributes a consumer inspected. The authors use this additional information to estimate a model of search at the brand-attribute level. Gardete and Hunter (2020) also study attribute-level search behavior using browsing data. They are able to observe attribute-level search because, in their data, different information about products is located on different webpages.

2.4 Developing a Search Model for an Empirical Application

Next, we discuss the decisions a researcher needs to make to develop a suitable empirical framework for a specific project. The goal of this section is to provide guidance on how to set up a search model framework based on the research question, the available data, and the institutional features of a particular setting.

One of the most important decisions the researcher has to make is to decide which information consumers are searching for; that is, the researcher has to choose whether a price, a match-value, or a multiple-characteristics search model is most appropriate in her empirical context.[7] To this end, the researcher needs to assess which product attributes are immediately observable to consumers and which product attributes are hidden or can only be accessed with additional effort. For example, when estimating demand for an infrequently purchased product sold on an online retail platform, price information is typically easily observable because it is usually displayed on product list pages. However, the consumer can only learn information on product material, country of origin, size, or review content when she visits a product-detail page. In this empirical context, a match-value search model is likely appropriate where the match value would capture all the information a consumer learns when visiting the product-detail page. In other empirical contexts, a price search model might be more appropriate. For example, when modeling demand for a frequently purchased product, such as cereal or detergent, in an offline context, consumers typically know the relevant product attributes but need to search for prices due to promotions. Similarly, a price search model is more appropriate if a consumer has decided which product to buy but needs to visit different retailers to find the best price.

Another decision the researcher has to make is to determine whether observed consumer behavior is compatible with the Weitzman (1979) sequential search model or whether an amended

[7]The multiple-characteristics search model requires the researcher to assume consumers know the joint distribution of multiple characteristics. Arguably, this assumption is a stronger one than presuming consumers know the distribution of one characteristic.

sequential search model or a different model altogether would better describe it. For example, the Weitzman (1979) model requires the assumption that consumers have rational expectations about the distribution of uncertainty. Such an assumption is appropriate when the consumer has prior experience with a category, but less so when the consumer is purchasing for the first time (or after a long break). Another critical building block of the Weitzman (1979) model is the assumption of independence of draws for the component of utility that is revealed after search. It implies the consumer only learns about the utility of the searched product, but does not obtain any information about the utilities of the unsearched products. For example, this assumption likely does not hold when products share common characteristics that consumers learn about through search (see, e.g., Gardete and Hunter 2020 on how to model consumer search in such a situation).

A third decision the researcher has to make is which institutional details to incorporate in the model and which ones to ignore. The decision should be guided by their importance for the research question and their impact on the consumer's shopping and purchase process. For example, online retailers typically show products as a ranked list on a screen. Taking rankings into account is important on large-screen devices where 30+ products are shown on a screen. However, one could argue rankings can be ignored in mobile commerce where typically only two to six products are shown on a screen. A second example is a paper by Lam (2023), who studies how the dual role of Amazon as both a platform and a retailer affects consumers and third-party sellers. To answer this question, Lam (2023) needs to model the impact of the "BuyBox" (which assigns one seller as the default) on consumer search, because this default option is how Amazon directly competes with third-party sellers for the sale of a product when both entities are selling it.

To summarize, the Weitzman (1979) model provides a natural starting point when the researcher is interested in estimating demand with consumer search. However, contrary to demand estimation under the assumption of perfect information, the researcher needs to make an assumption about what consumers learn while searching. The researcher also needs to assess whether the empirical setting is compatible with the Weitzman (1979) framework or whether a more complicated model is required. Finally, the researcher has to decide which market features need to be modeled explicitly and how to incorporate them in the search model framework.

2.5 What Can Retailers Learn from Search Data?

Based on the building blocks discussed above, the next three sections outline three broad areas of research where search data can be helpful. We first show search data can be used to inform a retailer's marketing decisions, which require an understanding of consumers' preferences. Two retailer decisions are particularly difficult to make without the aid of search data: First, retailers need to know substitution patterns to set profit-maximing prices. Learning substitution patterns can be difficult for many retailers, especially in online settings where large assortments of products are common. Second, targeted marketing activities such as coupons are often based on demographic variables and information on consumers' past purchases (see Rossi and Allenby 1993). However, in online retail settings for infrequently purchased products, such variables are often not available.

We show pre-purchase data can provide additional information on consumer preferences and thus can be used to inform these core marketing decisions.

Next, we turn to an analysis of how retailers can influence the search process. Broadly speaking, retailers have various tools at their disposal that can make certain products more salient to consumers, such as the preferential placement of products in a physical store or a high ranking on an online search-results page. Decisions regarding how to guide consumers' search process are particularly important when the number of available products is large and consumers are therefore likely to only discover and consider products that are more easily accessible. We refer to a broad class of interventions that can influence the search process as "store / webpage design decisions" and discuss what kind of data are required to analyze these retailer decisions. We then show how a search model framework can be used to compute consumers' choices, retailer profits, and consumer welfare under different marketing strategies. For example, the search model framework enables an analyst to find the profit-maximizing product ranking for an online retailer and to assess whether retailer incentives are aligned with consumer welfare. The latter issue has recently received attention in the debate about retailers' "self-preferencing" by making their own private-label products more salient to customers (Farronato et al. 2023; Lam 2023). We also discuss how search data can provide new insights on the impact of advertising, by allowing the researcher to observe at what stage of the purchase funnel advertising influences consumers' choices.

Finally, retailers operate in an environment where detailed information about products is increasingly available to consumers, for example, due to the emergence of price-comparison websites. Retailers therefore need to understand how the market equilibrium changes when search costs decrease due to easier access to information. In section 5, we discuss theoretical and empirical findings that show search costs can lead to both an increase or a decrease in equilibrium prices, depending on certain features of the market. We also discuss other equilibrium market outcomes such as advertising provision and store design.

3 Using Search Data to Learn Preferences

To gain an understanding of consumer preferences, the most common approach is to estimate some form of demand model using historic data on consumers' purchases. In this section, we recap how demand estimation is typically implemented using only purchase data and then discuss how additional information about preferences can be gleaned from search data.

3.1 Background: Choice Models

When estimating a demand model based on purchase data, a researcher typically posits that a consumer i obtains a given level of utility when purchasing product j[8].

$$u_{ij} = \boldsymbol{X}'_j \boldsymbol{\beta}_i - \alpha_i p_j + \mu_{ij}, \tag{3}$$

where p_j denotes price and $\boldsymbol{X}_j$ denotes a vector of product characteristics and can include product fixed effects and physical product characteristics. Finally, μ_{ij} denotes a taste shock that is iid across consumers and products. Integrating out over the taste shocks[9] (and possibly other stochastic elements of utility) yields expressions for choice probabilities, which are then used to form the likelihood. The model is estimated by finding the parameters that generate predicted choice probabilities that most closely match the empirical realizations, that is, maximize the likelihood function. Although many settings exist in which researchers estimate more complicated models of demand that deal with quantity choice or dynamic considerations, such as stockpiling, we focus on the workhorse static discrete-choice model because of its wide usage and because of the close relationship to models of consumer search, which we describe below.

Depending on the research question or marketing decision one wants to address and the type of data available, a specific parameterization of the utility function can be estimated. We focus on two applications: an understanding of substitution patterns between products and the estimation of heterogeneous preferences across consumers that form the basis for targeted marketing actions. Turning to substitution patterns first, a typical approach is to allow for heterogeneous preferences over characteristics, which leads to substitution patterns where products that are more similar in terms of the observed characteristics $\boldsymbol{X}_j$ have larger cross-price elasticities. Berry et al. (2004) note secondary choice data indicating the second-most preferred product, typically obtained from surveys, are particularly helpful for estimating heterogeneous preferences, because they permit the researcher to observe along which dimensions the consumer's most preferred and second-most preferred products are similar. As we show below, search data analyzed through the lens of the sequential search model provide information about preferences akin to the information contained in such secondary choice data. A second application of choice models is to focus specifically on estimating preferences at the individual consumer level. Allenby and Rossi (1999) argue such an analysis is particularly important for many applications in marketing because individual-level estimates are a prerequisite for designing targeted marketing strategies such as targeted coupons, which are common in retailing.

[8]If a researcher has access to panel data with repeated observation for each consumer, a time subscript t can be added to the utility function.

[9]Taste shocks are usually assumed to be normally (extreme value) distributed, which leads to probit (logit) expressions for choice probabilities.

3.2 Consumer Search & Substitution Patterns

Consumer search data allow the researcher to observe which products a consumer considered before making a purchase. As described in section 2.2, a researcher typically assumes a utility of the following form:

$$u_{ij} = \delta_{ij} + \varepsilon_{ij} = \left(\boldsymbol{X}_j'\boldsymbol{\beta}_i - \alpha_i p_j + \mu_{ij}\right) + \varepsilon_{ij},$$

which differs from the utility in a perfect-information choice model presented in equation (3) only due to the presence of the additional component ε_{ij}, which is discovered after search.
Moreover, a consumer will search products in decreasing order of reservation utility given by $z_{ij} = \delta_{ij} + g(c_i)$. When search costs are constant across products, reservation utilities are equal to the pre-search utility, δ_{ij}, plus a term that does not vary across products and thus does not impact the ranking of reservation utilities. Therefore, consumers will search products in decreasing order of their pre-search utility. Depending on the length of the search spells, the researcher will observe the first, second, third, and so on highest-utility options for each consumer. Through the lens of the sequential search model, data on the search sequence therefore take the same form as secondary choice data in a perfect-information choice model.[10]

It follows that the arguments regarding secondary choice data and the information they provide about preferences directly carry over to search data. The intuition is that consumers who care strongly about a specific product characteristic will only search products with high values of that characteristic.[11] Bronnenberg et al. (2016) provide empirical support for the usefulness of search data as second-choice data by showing products in a consumers' search set tend to be similar in terms of their characteristics. Search data have also been used in a more descriptive fashion as a predictor of market structure, by using co-search patterns as a basis for perceptual maps (Kim et al. 2011, Ringel and Skiera 2016). Although the perceptual-map approach is not based on an explicit model of optimal consumer search behavior, it does indirectly leverage the search model insight that frequently co-searched products are products with a high degree of substitutability.

Although the idea that search patterns are informative about substitution appears in some early empirical search papers (e.g., Kim et al. 2010), the focus of most consumer search papers has not been to estimate cross-price elasticities. Only recently have a few papers started to use search data specifically with the goal of estimating flexible substitution patterns. Amano et al. (2022) use search data from a retailer selling home improvement products and estimate product-pair-specific correlations in search propensities. Contrary to a characteristics-based approach, the model in Amano et al. (2022) can therefore capture substitutability along dimensions that are not observed by the researcher.[12] Armona et al. (2021) apply a related idea to the market for

[10] The equivalence between search data and second-choice data only holds when search costs are homogenous across products.

[11] An important assumption is that the characteristic is known prior to search. A characteristic whose value is only discovered after search can, by definition, not influence the search order.

[12] The paper uses a consideration-set framework, rather than a model of consumer search, but the general idea could, in principle, be implemented within a sequential search framework. However, a two-stage consideration-then-choice framework is computationally lighter.

hotels. They use a search model to estimate latent characteristics over which consumers have heterogeneous preferences. The logic behind their approach is similar to the second-choice logic described above. Namely, if two products are often searched together, the model will rationalize the co-search behavior by assigning a high value to a latent characteristic present in both products, so that consumers who value this characteristics will tend to search both products. Contrary to Amano et al. (2022), Armona et al. (2021) do not estimate product-level correlations, but instead estimate a lower-dimensional representation of those correlations via the latent-characteristics structure. This approach can be especially valuable when assortments are large, because it lowers the number of parameters that need to be estimated and can increase efficiency. In a second step, Armona et al. (2021) then use the inferred characteristics as an input in a discrete-choice demand model.

In summary, search data analyzed through the lens of a sequential search model or a related framework play a similar role to secondary choice data, which are known to help estimate heterogeneous preferences over product characteristics in perfect-information demand models. Moreover, because search data tend to be significantly more abundant than purchase data, they have recently been used to estimate similarity along *unobserved* dimensions by estimating either a latent-characteristics model or an unconstrained correlation structure.

3.3 Using Search Data for Targeted Marketing

Apart from its value for understanding the shape of the aggregate demand function and, in particular, cross-price elasticities, search data can also be helpful for identifying individual-level parameters. Similar to the estimation of consumer-level parameters from purchase data, these estimates can then be used to derive optimal targeted marketing strategies.

Jiang et al. (2021) use search data to derive better retargeting strategies for consumers who searched in a category but did not make a purchase. One of the empirical patterns we discussed in the introduction—the fact that conversion rates in many online markets are relatively low—is a key motivation for the study. The authors show that information on the set of products a consumer searched before leaving the platform without a purchase can be useful to improve a firm's retargeting strategy. They also show that information on search behavior is more valuable than information on consumer demographics.

Morozov et al. (2021) use panel data on consumer search behavior from an online cosmetics retailer and are, to the best of our knowledge, the first paper to observe consumers repeatedly searching and purchasing in the same category. The authors show that modeling search behavior leads to lower estimates of preference heterogeneity across consumers. Intuitively, search cost can lead to high choice persistence (repeated purchases of the same product) because consumers do not search beyond their most preferred product. In a model without search, high persistence in choice instead needs to be rationalized by strong heterogeneity in preferences. Apart from removing bias, search data also lead to more precise estimates of consumer-level parameters and therefore to more profitable targeting strategies. In their setting, the authors show that profits from targeted pricing increase by 9%, on average, and can increase by as much as 15% for some brands when search data are used.

Finally, Padilla et al. (2019) use search data to predict consumer demand for flights. They argue that, in many settings, such as hotels and flights, firms only have access to sparse purchase information, and additional information on the customer's journey can therefore help firms better understand consumer preferences. The paper emphasizes the importance of context heterogeneity in the market for flights, such as heterogeneity for business versus leisure flights. The paper also makes use of search-query data that contain information about the destination, date, and other trip characteristics. The authors show that additional information from product searches and queries leads to an improvement in model predictions regarding purchase incidence and the characteristics of the purchased product.

The above papers demonstrate search data can provide helpful information for targeted marketing, especially in settings in which consumers purchase infrequently, such as in many online settings, and where consumers often engage with a category by searching products but ultimately do not purchase.

4 How Retailers Can Influence Search Behavior

A second area where consumer search data and a search model framework are particularly useful is the analysis of marketing tools that can affect consumers' search behavior. As we described in the introduction, most empirical studies on consumer search find consumers consider only a very limited set of products. Therefore, understanding how retailers can impact search behavior to ensure consumers consider their products is likely of first-order importance to companies. Before turning to specific tools that retailers can use to influence search behavior, we outline how changes in search costs influence behavior in a search model, how the impact of marketing decisions on search costs can be identified, and how the sequential search model can be used to analyze counterfactual marketing strategies.

To understand how a retailer's marketing decisions can affect consumer search behavior, briefly recapping the main equations governing search behavior in the sequential search model outlined in section 2.2 is instructive. Consumers will search products in descending order of reservation utility $z_{ij} = \delta_{ij} + g(c_{ij})$. Because $g(c_{ij})$ is a decreasing function of search cost, an increase in a product's search costs will lower its reservation utility and decrease the likelihood that the product will be searched. Recall that utility and search costs are typically parameterized as follows:

$$\begin{aligned} u_{ij} &= \left(\boldsymbol{X}_j' \boldsymbol{\beta}_i - \alpha_i p_j + \mu_{ij}\right) + \varepsilon_{ij} \\ c_{ij} &= \boldsymbol{Z}_j' \boldsymbol{\gamma}_i, \end{aligned}$$

where p_j denotes price and $\boldsymbol{X}_j$ and $\boldsymbol{Z}_j$ denote vectors of product characteristics that enter preferences and/or search costs. Both sets of variables can include product fixed effects, physical product characteristics, and other marketing variables, such as product rankings on a webpage or advertising, that are under a firm's control.

One key issue that comes up in this setting is how to separate the impact of a particular marketing variable on search costs versus preferences. For example, advertising could in principle be seen as shifting search costs by making certain products more salient to the consumer or as shifting preferences by increasing the consumer's perceived utility from the product.[13] Because search costs and preferences have a different impact on search and purchase decisions, one can separately identify the impact of a given marketing variable on preferences and search costs. The reservation-utility formula in equation (2) shows a decrease in search costs and an increase in (pre-search) utility both shift the reservation utility in the same direction. However, after stopping to search, the consumer will choose the highest-utility product based solely on its utility. Search costs are not relevant at this point of the choice process. Intuitively, increasing utility will increase the search and purchase probability, whereas lowering search costs will increase search but affect purchases less. Ursu et al. (2023a) provide a formal identification argument for the separate identification of search costs and preferences. Ursu (2018) implements a test that follows a similar logic and shows rankings impact search decisions, but not conversion, conditional on search. She therefore argues rankings should enter search costs and not utility.

Regardless of whether a given variable enters utility or search costs, one needs random variation to estimate its causal impact. The concerns around endogeneity are not unique to search models and are similar in spirit to the issue of price endogeneity in a standard demand model setting. For instance, the marketing variables of interest might be correlated with product quality in specific ways: higher-quality products tend to be ranked higher on a webpage because they are deemed more relevant to consumers. In such a situation, the estimated effect of rank on search costs might be biased upwards because high-ranked products are searched earlier because of their rank as well as because of their higher quality. Similar arguments can be made for all the other marketing variables discussed below that are under the firm's control. The likely endogeneity of marketing variables represents a challenge for researchers because they are either left with quantifying correlational relationships, having to model the firm's decision-making, or must find exogenous/experimental variation.

Once the effect of a specific marketing action on search costs has been inferred, we can use the search model framework to compute relevant counterfactuals. For example, counterfactual purchase probabilities can be calculated and, together with information on mark-ups, used to compute counterfactual profits. Similarly, computing welfare for different values of the marketing variables is possible. Contrary to perfect-information demand models, welfare calculations also need to take into account search costs under different counterfactual scenarios. Consumer surplus in the search model context is given by

[13] Additionally, marketing variables can also indirectly affect consumer search via changing consumers' awareness sets. We discuss these effects in detail in the context of advertising in section 4.3.

$$CS_i = \frac{1}{\alpha_i} \left(u^*_{ij} - \sum_{k \in S_i} c_{ik} \right) ,$$

where u^*_{ij} denotes the utility of the chosen option and the second term denotes the total search costs the consumer incurs by searching the set of products S_i. Search data combined with a structural framework such as the sequential search model therefore allow researchers to analyze the impact of counterfactual marketing strategies on both retailer profits and consumer welfare. For example, an online retailer can derive the optimal product ranking that maximizes their profits by assessing how different rankings affect purchase probabilities and profits. Similarly, one can assess how a profit-maximizing ranking impacts consumer welfare, which is a question that regulators often care about.

Based on the conceptual framework outlined above, we next turn to specific marketing tools that have been studied using a model of consumer search behavior. We note the search model framework is very general and can be used to analyze any variable that shifts search costs. Below, we focus on the most commonly studied marketing tools.

4.1 Rankings

One of the marketing tools that has received the most attention is product rankings on online platforms. An early paper that analyzes rankings through the lens of a search model is Ursu (2018). The author uses data from a field experiment run by the online travel agent Expedia that exposed a sample of consumers to hotels displayed in a randomized order. Using these experimental data, Ursu (2018) shows rankings influence search decisions, but not conversion conditional on search. She therefore argues rankings should enter search costs and not utility. To the best of our knowledge, most papers that study rankings now take as given that rankings should enter search costs but not utility.

In terms of magnitude, Ursu (2018) finds rankings have a large effect on which products consumers search and, by increasing the probability of search, also positively impact purchase probabilities. She documents that the click probability decreases from 12% to 9% between the first and second rank position and further decreases to around 4.5% at position 10. Such large ranking effects are consistent with the empirical fact that consumers tend to search relatively little and therefore are most likely to click on products that are salient in the ranking of search results. The search model also allows the author to quantify the magnitude of position effects in monetary terms. Interestingly, she finds the position-effect estimate is substantially lower than other studies that rely on non-random variation in rankings. This finding is consistent with the idea that position effects are overestimated with observational data, because more popular products tend to be ranked higher.

Given that rankings have an economically important impact on search and purchase behavior, a natural question is how changes in ranking algorithms affect retailers' profits. One paper in this vein is Ghose et al. (2014), who show a utility-based ranking improves revenues by 5% over the default ranking and produces higher revenues than any other considered ranking, such as ranking products by their purchase probabilities, prices, number of reviews, and other features. Other papers have suggested ranking algorithms that optimize specific objectives. For instance, De los Santos and Koulayev (2017) propose a ranking method that optimizes click-through rates: it takes into account that, even though the intermediary typically knows very little about a consumer, the intermediary observes search-refinement actions as well as other search actions, which allows it to learn consumer preferences. The authors find their proposed ranking method almost doubles click-through rates for a hotel booking website in comparison to the website's default ranking. These findings show that because rankings affect consumers' search and purchase behavior, optimizing rankings can have a large impact on firms' revenue and profits.

Apart from affecting retailers' profits, the impact of ranking algorithms on consumers has been of interest to policymakers. One potential worry of regulators is that retailers might rank high-margin products very highly because they generate profits for the firm, but such a ranking could decrease consumer welfare. Several recent papers come to different conclusions about the alignment of firm incentives and consumer welfare. Greminger (2022) estimates a model of discovery and search based on the framework in Greminger (2021). He then uses the estimates of the model to derive the revenue-maximizing ranking and shows such a ranking also leads to an increase in consumer welfare relative to the current status-quo ranking. Compiani et al. (2023) address the same research question using a different modeling approach that allows preferences and search costs to vary flexibly across products. Their empirical results show ranking products that have a high purchase value but low search value (products that are so-called "diamonds in the rough") can maximize consumer welfare, whereas a profit-maximizing strategy would require the platform to rank high-margin products higher. The paper argues rankings that maximize welfare and profits are therefore in tension with each other. Whereas Greminger (2022) and Compiani et al. (2023) investigate the potential tension between retailers' profit maximization and consumer welfare for uniform ranking algorithms, Donnelly et al. (2023) study personalized versus uniform best-seller ranking algorithms. They find the personalized ranking implemented by the platform they study increases both consumer welfare and retailers' profits compared with a uniform ranking, suggesting retailer incentives are aligned with consumer welfare in their setting.

To summarize, the three papers end up with conflicting findings regarding the alignment or tension of welfare and profit-/revenue-maximizing rankings. Given the policy relevance of this question, reconciling these findings in future work as well as characterizing the conditions under which consumer welfare will decrease or increase when retailers choose (personalized) rankings to maximize profits will be important. The potential tension between firms' incentives and consumer welfare is also at the heart of the discussion around "self-preferencing," that is, the more prominent display of a retailer's own products (Farronato et al. 2023,Lam 2023, Reimers and Waldfogel 2023). Although this discussion has focused mostly on online retailers, Dubé (2022) points out that similar issues arise in a brick-and-mortar setting where a retailer might give preferential shelf placement to its private-label products.

4.2 Store & Webpage Design

Rankings are only one decision that online retailers make to increase the saliency of some products. Retailers have many other tools at their disposal that affect the ease with which consumers can find certain products. In the online setting, retailers can influence how consumers navigate a webpage through tools such as rankings, recommendations, and product endorsements/badges. In physical stores, retailers decide where to place products and whether to highlight them with on-shelf displays. Most of these marketing tools are best thought of as altering consumer search costs, because they affect the saliency of products, but, arguably, do not directly affect consumers' preferences. Therefore, many of the insights from our discussion of rankings carry over to the analysis of other marketing tools that shift search costs. We singled out rankings because they have been studied more extensively, likely due to better data availability. The literature on other marketing tools and their impact on search behavior is sparser. Below, we highlight a series of papers that analyze these firm decisions through the lens of a search model.

Product recommendations, for example, displayed at the bottom of a product-detail page, are a common feature in online retail. The literature on the effects of product recommendations on consumer searches and purchases is sparse partly because researchers typically do not observe which products a retailer recommended and/or which recommendations a consumer saw. Moreover, retailers usually recommend products that have a high probability of being relevant to the consumer. This correlation between recommendations and preferences generates an endogeneity problem. Kim et al. (2011) document that product recommendations are associated with products that are more frequently searched together. However, their data do not contain random variation in recommendations. Korganbekova and Zuber (2023) observe recommendations and run a randomized experiment that removes some recommendations from product pages. Although the primary focus of the paper is on personalized rankings rather than recommendations, it is the only paper that we are aware of containing experimental variation in recommendations.

Badges are another marketing tool commonly used by online retailers. For example, Amazon highlights specific products on a search-results page using badges such as "Amazon's Choice" or "Best Seller." Bairathi et al. (2023) study how badges affect consumer search and purchase decisions and find the highlighted product benefits from the badge. Bairathi et al. (2023) also analyze spillover effects (a topic we cover in more detail in the context of advertising) and find that products that are spatially close on the screen to the highlighted product experience a decrease in searches, whereas products located farther away benefit from the introduction of badges. Apart from Bairathi et al. (2023), a broader literature on badges and quality certification (e.g., Elfenbein et al. 2015, Hui et al. 2016) exists that does not use search data.

A small number of papers investigates the impact of different webpage design choices. Gardete and Hunter (2020) estimate a search model in which consumers search over alternatives with multiple characteristics. A unique aspect of their clickstream data from the website of a used car seller is that information on different characteristics is shown on different pages, enabling the authors to observe which specific characteristics a consumer searched. In counterfactual exercises, Gardete and Hunter (2020) predict the effects of different website designs. The authors find different information-design policies have moderate effects on consumers but a sizeable impact on seller profits. Zhang et al. (2023) estimate a model of discovery and search based on Greminger (2021) using data from an apparel retailer's mobile app store. They then use their estimates to study the effects of counterfactual store changes. For example, the authors find consumers value the option to only loog at items that are on sale: it provides incremental sales representing about 4% of revenue. Gu and Wang (2022) investigate the question of how much information to reveal at different layers of a website, that is, whether to display price in search results or only after clicking through to the product-detail page. The authors find revealing prices in the outer layer leads to higher welfare, whereas not revealing prices increases revenue.

In the context of brick-and-mortar retail, we are aware of only two studies that analyze the impact of store design decisions on consumer search and purchase behavior. Using a unique dataset containing nine layout changes in a grocery store and sales from two control stores, Ranjan et al. (2017) document that layout changes significantly affect sales. The authors formulate a model of attention/consideration, purchase, and learning and find the location of a category significantly affects whether a consumer considers it. Furthermore, Ranjan et al. (2017) also note the existence of attention spillover effects: being located adjacent to a popular category increases the consideration probability for the focal category. Xu et al. (2023) also study the impact of changes in product locations within a set of grocery stores, but they do so with data not only on sales, but also on consumers' search activity within a store using eye-tracking data. The authors show layout changes affect consumer search behavior and thereby have an impact on sales. In particular, the paper finds consumers search longer in response to a layout change and that they are more likely to search and buy products that are close to either the old or the new location of their previously purchased products.

In summary, although the literature on the impact of other marketing tools on search is conceptually similar to studying the impact of rankings via a search model, it is relatively scarce due in large part to issues of data availability and a lack of random variation in the marketing tools. For example, recommendations are rarely observed in standard clickstream data and, to the best of our knowledge, only Korganbekova and Zuber (2023) base their analysis on experimental variation in recommendations. Similarly, observing product placement as well as variation in placement in a physical store is rare. To make progress on the analysis of the various store / webpage design tools described above, better data, ideally containing random variation in the specific marketing variable, need to be collected. No particular conceptual obstacle to studying these questions exists, and the analysis of rankings using a search framework can be directly transposed onto the study of other variables.

4.3 Advertising

Advertising is one of the most commonly employed marketing tools, and a large literature studies the impact of advertising on consumers' purchases. In this section, we focus on the impact of advertising along the purchase funnel, which becomes observable with pre-purchase data. For example, in the context of online retail, search data permit the researcher to observe whether advertising affects a consumer's clicking decision and/or a consumer's purchase decision conditional on clicking. Our discussion of advertising differs somewhat from the above discussion of other marketing variables. Marketing tools such as rankings or recommendations are usually modeled as variables that alter search costs. However, how advertising affects consumer behavior is not a priori clear. Advertising may lower search costs by making the advertised product more salient or it might directly increase the utility from purchasing the advertised product. Several studies measuring the impact of advertising also include an awareness stage in which advertising might affect whether consumers know of the existence of a product.

Similar to the other marketing variables described above, endogeneity concerns also arise in the case of advertising. Theses concerns have been addressed by using random variation in advertising (e.g., Morozov and Tuchman 2023), by using quasi-experimental approaches (e.g., Tsai and Honka 2021), or by using a control function inside a structural search model that exploits variation in arguably exogenous variables that impact advertising (e.g., Honka et al. 2017).

Honka et al. (2017) quantify the effects of advertising along the purchase funnel for savings accounts. They use variation in advertising costs to address the endogeneity of advertising exposure and find advertising has a large indirect effect on choice via increasing awareness and only a small direct effect on choices conditional on awareness. Tsai and Honka (2021) study how advertising affects consumers along the auto insurance purchase funnel. The authors account for advertising endogeneity using variation in advertising across media market borders (Shapiro 2018).[14] They find advertising increases awareness but has no significant effects on searches conditional on awareness, suggesting advertising primarily affects the awareness stage of the purchase funnel. Morozov and Tuchman (2023) set up an online e-book store to run field experiments, and they find advertising affects both search and purchase decisions, with the effect on searches being larger. In the context of feature advertising for a supermarket, Seiler and Yao (2017) show advertising leads to higher sales but does not increase traffic to the advertised category. Contrary to the various studies of online retail, advertising in physical stores therefore appears to only affect consumers at the purchase stage of the conversion funnel.[15]

Advertising might lead to spillover effects depending on where in the purchase funnel advertising affects behavior. Advertising that increases awareness for a product could, for instance,

[14] Shapiro (2018) first proposed the use of the border strategy to address advertising endogeneity concerns. This strategy exploits the discontinuity in TV advertising along the borders of television markets (DMAs). It rests on the assumption that consumers on both sides of the border of a DMA are similar but are exposed to different TV advertising. The advertising effects are then identified by the differences in how consumers on both sides of a border react to differences in advertising.

[15] In a related paper, Ursu et al. (2023b) model how online display ads can expand consumers' awareness sets before and during the search process.

increase awareness for other similar products. Sahni (2016) shows advertising spillovers on an online restaurant-search website between restaurants that belong to the same category/cuisine. Although he does not estimate a structural search model, his analysis is motivated by a model in which advertising affects awareness of products with particular characteristics.[16]In the context of a Weitzman (1979)-style model, modeling spillovers by allowing advertising to decrease search costs not only for the focal product but also for other similar products would also be possible.[17] To the best of our knowledge, no structural search paper has modeled spillovers in this fashion.

Several papers have examined spillovers (or their absence) using a reduced-form approach. Seiler and Yao (2017) do not find evidence of advertising spillovers to other categories in close physical proximity in a physical store environment. Within a product category, the authors only find spillovers between products that belong to the same brand. They hypothesize that spillovers in a physical store might be limited because consumers' paths through a store are difficult to influence through advertising. In the online context, the findings are mixed with Sahni (2016) and Liang et al. (2019) documenting spillover effects between similar products, whereas Fong (2017) shows targeted ads lead to more searches of the advertised product at the expense of searches for non-advertised similar products in the case of an online wine retailer. Morozov and Tuchman (2023) also find no evidence of advertising spillovers to similar products in an online bookstore.

A small set of recent papers have started to investigate the effects of different advertising content on consumer search decisions. Tsai and Honka (2021) show informational advertising increases aided awareness, whereas non-informational advertising increases unaided awareness in the car insurance market. Morozov and Tuchman (2023) analyze three types of ad content for e-books: plain ads with no information, ads with information about a horizontal characteristic (book genre), and ads with information about a vertical characteristic (price). The authors find price advertising increases search among all consumers. However, genre advertising induces some consumers to search the advertised book and others to reject it without search. These patterns suggest advertising affects consumer search behavior differently depending on the content of the ad.

In summary, most evidence points toward advertising having a large impact on consumers' awareness of products and less of an influence on choices conditional on awareness. In terms of a behavioral mechanism, this pattern suggests an informative rather than a persuasive role of advertising in many settings. The one notable exception is Seiler and Yao (2017), who document an impact of advertising only at the purchase stage of the conversion funnel, which might point to a difference in how advertising affects consumers in an online versus offline setting. The evidence on spillover effects is more mixed, with only a subset of papers findings evidence for spillover effects to similar products. The existing studies do not point to a clear pattern wregarding the circumstances under which spillovers arise.

[16]Similarly, Liang et al. (2019) document advertising spillover between products with similar characteristics in the market for mobile apps.

[17]If advertising leads to some form of learning across products, the independence assumption regarding the error revealed after search would be violated, and the Weitzman (1979) framework could no longer be used.

5 How Search Frictions Affect Equilibrium Outcomes

In the preceding section, we discussed several advances made by prior work in trying to understand how firms' marketing actions impact consumer search and purchase decisions in a partial equilibrium fashion, that is, without an explicit model of how firms optimally choose these marketing variables. To understand how markets function in the presence of search frictions, we also need to consider how firms optimally behave when facing consumers who engage in costly search. In this section, we therefore turn to outcomes of firm-consumer interactions when both firms' and consumers' decisions are jointly determined in equilibrium.

In what follows, we describe the theoretical results pertaining to equilibrium prices, store design, and advertising and discuss relevant empirical applications. In general, most empirical work on consumer search has focused on the demand side, and the empirical literature that studies equilibrium outcomes is sparse.

5.1 Equilibrium Pricing

Equilibrium price setting in the presence of search costs can be characterized by extreme outcomes, as illustrated by the well-known "Diamond paradox" (due to Diamond 1971). In the Diamond (1971) model, consumers have unit demand, a large number of firms sell a homogeneous product, and consumers search to learn the prices firms charge. Each consumer starts at a firm and must pay a search cost to visit another firm to learn the price it charges. In this framework, the market completely collapses in equilibrium: the equilibrium price in the market equals the monopoly price; thus, no price dispersion exists. Without price dispersion, consumers do not need to search.

In contrast to the stark predictions from the Diamond (1971) model, an abundance of data have shown that prices, even for homogeneous products, differ across retailers; that is, price dispersion exists (Stigler 1961; Sorensen 2000; Hortaçsu and Syverson 2004; Hong and Shum 2006; Hitsch et al. 2021), and consumers frequently search more than one retailer. Many theoretical search models therefore explore ways in which the Diamond paradox can be avoided and price dispersion is generated in equilibrium.

Subsequent work has proposed two main mechanisms that lead to price dispersion as an equilibrium outcome: consumer and firm heterogeneity. Stahl (1989) and Stahl (1996) show consumer search-cost heterogeneity can lead to price dispersion. In these models, two groups of consumers exist: "shoppers," who have negative search costs, that is, enjoy searching, and "non-shoppers" with positive search costs. In this framework, price dispersion arises as firms employ mixed strategies in prices to cater to both groups of consumers. Similarly, Salop and Stiglitz (1977) contains two types of consumers: "informed" consumers, who know the distribution of prices and can always identify the lowest-priced firm, and "uninformed" consumers. Similar to the Stahl (1989) and Stahl (1996) models, in equilibrium, different firms sell to different types of consumers, leading to price dispersion in the market. In comparison, Reinganum (1979) and MacMinn (1980) investigate how firm production-cost heterogeneity can lead to price dispersion. For instance, Reinganum (1979) proves the existence of price dispersion in equilibrium when firms have different marginal costs and consumers have elastic demand.

An important counterfactual that is of interest to researchers, policymakers, and managers is whether a decrease in search costs leads to an increase or a decrease in equilibrium prices. For example, the emergence of online price-comparison websites can be conceived as lowering consumers' search costs. The literature has derived ambiguous results regarding the relation between equilibrium price levels and search costs. On the one hand, in Diamond (1971), Stahl (1989), and Stahl (1996), prices can increase in search costs. In Diamond (1971), this increase happens because the introduction of even an infinitesimal search cost results in prices jumping from perfectly competitive levels to the monopoly level. In Stahl (1989) and Stahl (1996), prices can increase in search costs because of the existence of two types of consumers ("shoppers" and "non-shoppers"), who differ in their search costs: as the search costs of non-shoppers decrease, prices decrease and converge to marginal cost.

On the other hand, more recent work shows equilibrium prices can also decrease in search costs (Armstrong and Zhou 2011; Choi et al. 2018; Ding and Zhang 2018; Garcia and Shelegia 2018; Haan et al. 2018). This type of result generally arises when products are differentiated, consumers search to learn about an attribute other than price, and consumers search options sequentially. For example, in Haan et al. (2018), two firms sell a horizontally differentiated product with two attributes: one that is observable without search and another one for which the consumer pays a search cost to learn about. In addition, products differ in their prices and firms can make these prices observable without search, thereby directing the search process. The authors show that when prices are observable, a higher search cost implies more competition between firms to be searched first by a consumer and therefore lower prices. In other words, firms are willing to lower prices more when search costs are higher, because they know consumers will then be less likely to visit the other firm.

Overall, the theoretical literature suggests settings in which consumers search over prices lead to equilibrium prices that increase in search costs. However, when prices are observable prior to search, a decrease in search costs can lead to higher prices in equilibrium. In many online settings, the latter case appears to be more relevant. For example, on the typical online retail webpage, prices are observable on the search-results page, but a consumer needs to visit a product-detail page (i.e., search) to gather information about other product attributes. This result is important for managers and policymakers because it shows consumers may be hurt by a decrease in search costs.

Turning to empirical work, a small set of papers has studied the equilibrium relationship between price levels and search costs. In line with the ambiguous predictions from the theory literature, empirical papers have found evidence for both a positive and a negative relation between price levels and search costs. For example, Brown and Goolsbee (2002) look at the impact of the internet on the price of life insurance in the 1990s. They posit that the internet has reduced search costs by enabling consumers to more easily compare products. The authors find the internet has led to an 8%–15% reduction in prices. Studying the new car market in the Netherlands, Moraga-González et al. (2023) show reducing search costs, for example, by allowing at-home test drives, results in lower prices. By contrast, in settings in which prices can be more easily observed prior to searching, empirical work generally finds lower search costs lead to higher prices. For instance, when studying supermarkets in the UK, Wildenbeest (2011) shows higher search intensity can lead to higher prices. The empirical literature therefore supports the key distinction between prices being observable before or only after search as the main determinant for the direction of the relationship between search costs and equilibrium prices. We note only Brown and Goolsbee (2002) directly estimate the impact of an exogenous decrease in search costs on equilibrium prices. The other papers cited above estimate models of consumer search and supply-side price setting and then assess the impact of search-cost changes in counterfactuals.

5.2 Other Marketing Tools

To the best of our knowledge, empirical papers studying equilibrium outcomes focus solely on how search frictions affect equilibrium prices. In principle, all marketing tools that we discussed in section 4 could also be studied in a general equilibrium framework. However, such a study has not been undertaken, because of limited theoretical work, a lack of good data, and the difficulty of modeling supply-side behavior. For example, the theoretical literature on equilibrium advertising outcomes often only examines a few selected forms of advertising (e.g., price advertising or advertising that solely raises awareness). Due to the lack of empirical work, we confine ourselves to a brief overview of theoretical work in the areas of equilibrium store design and equilibrium advertising. Some of these theoretical papers could provide a template for future empirical work.

In the context of store design, Petrikaitė (2018) demonstrates that a multi-product firm that is able to choose both search costs and prices will obfuscate some of its products to maximize profits. The author shows that in equilibrium, the firm will set a higher price for the product that it does not obfuscate and consumer welfare will be lower under obfuscation. Ursu and Dzyabura (2020) study how to optimally order products in a store when search costs depend on the product location. The authors find the retailer will make lower-valuation products more prominent, because products with higher valuations will be searched even at higher search costs. Related to the discussion around the welfare effects of rankings presented in section 4.1, the limited theoretical work in this area suggests optimal firm policies might lead to lower consumer welfare in the presence of search costs.

Turning to advertising, theoretical work has typically examined settings in which consumers can decide whether to search after receiving an ad from a firm in the first stage (Butters 1977; Robert and Stahl 1993; Anderson and Renault 2006, 2013; Haan and Moraga-González 2011; Mayzlin and Shin 2011; Shin and Yu 2021). Some of these papers only study price-advertising decisions, whereas others investigate advertising decisions when a firm can advertise both price and other content. Among the papers that focus on price advertising, Butters (1977) finds search only occurs if consumers receive no ads. In Robert and Stahl (1993), firms charge either high or low prices, and those that charge high prices only sell to consumers who are uninformed. Thus, both papers find that, in equilibrium, it is optimal for firms not to advertise to all consumers.

Anderson and Renault (2006) is one of a few papers that examine equilibrium advertising decisions in search markets when firms can choose from multiple types of advertising content. In the paper, a monopolist has to decide whether to advertise price and/or match-value information to consumers before they decide whether to search for the remaining information or to purchase the item when all information has been revealed through the ad. The authors show that it is optimal for the firm to only minimally advertise the match value or, alternatively, to advertise prices and partial match information. When prices are advertised, they decrease in search costs; that is, advertised prices are lower for higher search-cost levels. Mayzlin and Shin (2011) derive similar results but show a new mechanism: firms prefer to withhold information in order to encourage consumers to search. In a follow-up paper, Anderson and Renault (2013) investigate the optimal mix of advertising content (quality, price, and horizontal match) for a search good. The authors find lower-quality firms need to provide more information than higher-quality firms. Furthermore, for a given quality level, quality information is revealed first, followed by price information and then by horizontal match information. Taken together, the findings from these papers indicate it might be optimal for firms operating in search markets to employ advertising that only partially reveals information about products.

6 Summary and Directions for Future Research

Our overview takes two stylized facts about search behavior as a starting point: consumers typically search relatively little, and, in many settings, substantially more search than purchase data exist. Based on these empirical patterns, we highlight three research areas for which search data can be particularly valuable.

The abundance of search data relative to purchase data can help researchers better estimate consumer preferences, which, in turn, can improve marketing strategies such as targeted campaigns. The nascent empirical literature has primarily focused on online retail settings and uses data on the identities of the products consumers searched before making a purchase. Other types of search data, such as information on search queries, and sorting and filtering decisions, have been used in only a small number of studies, due to a lack of good data and the need to develop appropriate model frameworks that go beyond the Weitzman (1979) sequential search model. To the best of our knowledge, no extant studies augment demand estimation with search data in a physical store setting, likely because of a lack of sufficiently granular data. Future research can build upon existing work by collecting better data on online and offline pre-purchase behavior, such as information from eye-tracking (e.g., Ursu et al. 2022), data on how consumers scroll through products on a webpage, or data on consumer activities on other websites prior to visiting the focal retailer (e.g., visiting independent review websites or other retailers). Incorporating such additional data will, in many cases, also involve the development of suitable modeling frameworks that can accommodate such data.

Second, a search framework coupled with data on consumer search behavior can be used to study the impact of store design decisions, such as product rankings, recommendations, or product placements in a physical store. Because consumers search few products, the impact of such decisions on search and, by extension, on purchases can be large. To study the effects of these marketing variables, one needs to observe the relevant variables and the data needs to contain plausibly exogenous variation that can be used to estimate their causal impact. However, many key variables are often not observed. For example, product recommendations displayed at the bottom of a product-detail page or information on physical store planograms and product placements are often unavailable. Product rankings on an online retailer's webpage are the one marketing decision that has received considerable attention recently due to better data availability. Interestingly, many studies in this area work with the same dataset from an experiment with random rank assignment (see, e.g., Ursu (2018), Compiani et al. 2023, and Greminger 2022). To push this research area forward, collecting data on additional variables that can influence search behavior would be necessary, and obtaining exogenous variation in these variables would be ideal. The latter can be achieved either by isolating arguably exogenous variation in historic data or by generating the requisite variation by collaborating with a retailer. This research direction in the context of physical stores is especially promising. Whereas previous research has examined the effects of store design decisions and product placements on purchases, we know very little about how store design and product placements affect consumer behavior earlier in the purchase funnel.

Advertising is another marketing variable that can influence search behavior. The increasing availability of pre-purchase data now allows researchers to study novel aspects of how consumers react to this core marketing variable. Observing search behavior is particularly useful for analyzing where in the purchase funnel advertising affects consumer behavior, which, in turn, can also provide guidance on possible spillover effects from advertising. The existing empirical literature points to advertising having large effects on consumers during the earlier stages of the purchase funnel, such as awareness or search. These results can be interpreted as advertising being mostly informative rather than persuasive in nature. Empirical findings regarding spillover effects are ambiguous and require further investigation to understand the conditions under which they arise. The impact of different advertising content along the purchase funnel has been studied in only a handful of papers (e.g., Tsai and Honka 2021, Morozov and Tuchman 2023) and thus represents another opportunity for future research. Based on such an analysis of the effects of different advertising content, the next step would be to study optimal advertising-content decisions.

Finally, retailers need to navigate an environment where consumers increasingly have access to more information about products. Therefore, they need to understand how changes in the information environment change equilibrium market outcomes such as prices and profits. The empirical research in this area is still limited, and most research analyzes changes in equilibrium prices indirectly by analyzing counterfactual outcomes when lowering search costs. Less work studies this question by analyzing observed changes in search costs, because events that alter search costs typically also affect other aspects of the market. In other words, similar to the challenges of studying marketing variables that shift search costs, obtaining exogenous variation is a key obstacle to the analysis of equilibrium outcomes under search frictions. Similar to price outcomes, retailers also must understand how non-price outcomes change in equilibrium when search costs change. To the best of our knowledge, no empirical work exists on equilibrium outcomes other than price.

Several key themes emerge from the discussion above: whereas the consumer search literature has been growing, ample opportunities are available for future research to expand upon the current state of knowledge. Two related avenues consist of adding supplementary data on other pre-purchase behavior and developing model frameworks that accommodate such data. Adding data on the sequence of searched products has been shown to improve retailer marketing strategies, such as targeted coupons, and adding further pre-purchase information will likely lead to additional improvements. A second major area for future research is the analysis of the whole toolkit that brick-and-mortar and online retailers have at their disposal to guide consumer search. In the online context, these tools involve product recommendations, placement on the homepage, and endorsement badges. In a physical store, decisions such as product placement and on-the-shelf displays can affect consumer search. To study these questions, researchers need to collect data on the relevant marketing variables and have access to (or generate) exogenous variation in those variables. Similarly, to study equilibrium outcomes, exogenous variation in search costs is required.

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