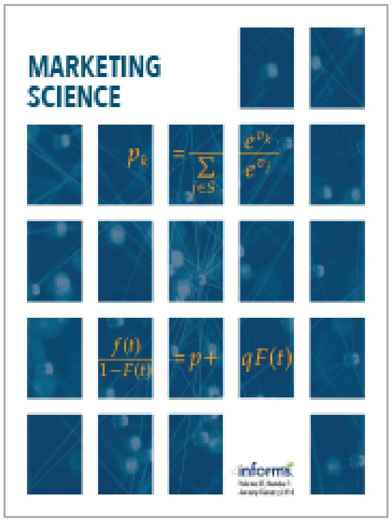


Marketing Science

Search Duration

Raluca M. Ursu, Qingliang Wang, Pradeep K. Chintagunta

informs
http://pubsonline.informs.org/journal/mksc

MARKETING SCIENCE
Vol. 39, No. 5, September–October 2020, pp. 849–871
ISSN 0732-2399 (print), ISSN 1526-548X (online)

Search Duration

Raluca M. Ursu,[a] Qingliang Wang,[b,*] Pradeep K. Chintagunta[c]

[a] Stern School of Business, New York University, New York, New York 10012; [b] School of Management, Northwestern Polytechnical University, 710072 Xi'an, Shaanxi, China; [c] Booth School of Business, University of Chicago, Chicago, Illinois 60637
*Corresponding author

Contact: rursu@stern.nyu.edu, https://orcid.org/0000-0003-2239-1498 (RMU); qingliang.wang@nwpu.edu.cn, https://orcid.org/0000-0003-4426-2769 (QW); pradeep.chintagunta@chicagobooth.edu, https://orcid.org/0000-0003-2854-5216 (PKC)

Received: August 22, 2018
Revised: June 17, 2019; October 31, 2019; January 5, 2020
Accepted: January 7, 2020
Published Online in Articles in Advance: July 31, 2020

https://doi.org/10.1287/mksc.2020.1225

Abstract. In studying consumer search behavior, researchers typically focus on which products consumers add to their consideration sets (the extensive margin of search). In this article, we attempt to additionally study how much consumers search individual products (the intensive margin of search) by analyzing the time they spend searching (search duration). We develop a sequential search model by which consumers who are uncertain (and have prior beliefs) about their match value for a product search to reveal (noisy) signals about it that they then use to update their beliefs in a Bayesian fashion. Search duration, in this context, is an outcome of the decision by a consumer to seek information on the same product multiple times; with a unit of time corresponding to one signal, the more the number of signals sought greater is the search duration. We also show how the model can be used to study revisits, a feature not easily accommodated in Weitzman's sequential search model. We build on the framework by Chick and Frazier for describing the optimal search rules for the full set of decisions consumers make (which products to search, for how long, in what order, and whether to purchase) and develop the model's empirical counterpart. We estimate the proposed model using data on consumers searching for restaurants online. We document that search duration is considerable, even when consumers search few restaurants, and that restaurants that are searched longer are more likely to be purchased. Using our model, we quantify preferences and search costs, as well as consumer prior beliefs, providing additional insights into consumers' search process. Finally, we develop managerial implications related to the amount of information companies should provide to consumers, given that this will affect search duration and thus search and purchase decisions.

History: Avi Goldfarb served as the senior editor, and Bart Bronnenberg served as associate editor for this article.
Funding: P.K. Chintagunta thanks the Kilts Center for Marketing at the Booth School of Business, University of Chicago for financial support. Q. Wang acknowledges financial support from the National Science Foundation of China [Grant 71402131].
Supplemental Material: Data and the online appendix are available at https://doi.org/10.1287/mksc.2020.1225.

Keywords: search duration • search with learning • revisits • optimal search rules • sequential sampling • online consumer search

1. Introduction

These days, consumers have access to a plethora of information, especially online. This additional information allows consumers to make better or more informed choices. At the same time, paying attention to this information is costly. To understand how consumers make choices in such an environment, previous work has devoted a considerable amount of attention to the question of which products consumers add to their consideration sets before making a purchase decision. We refer to this type of consumer search decision as the extensive margin of search. In contrast, relatively little is known about how much consumers choose to search individual products, or what we refer to as the intensive margin of search. However, examples of such search decisions abound including the decision to spend time searching a product, the decision to revisit a previously searched option to resolve further uncertainty about it, etc.

In this article, we develop a sequential search model that endogenizes not only the decisions to search and purchase a product but also the consumer's decision to spend time searching. In this model, consumers who are uncertain (and have prior beliefs) about their match value for a product, search to reveal (noisy) signals about it that they then use to update their beliefs in a Bayesian fashion. We model search duration as the consumer's decision to search the same product multiple times. This approach allows us to use the sequential sampling theory developed by Chick and Frazier (2012) to characterize consumers' optimal search rules. This model captures richer patterns of consumer search behavior, relating to not only search costs and consumer preferences but also their prior awareness of the product. We build on the work of Chick and Frazier (2012) and develop the model's empirical counterpart.

Our approach differs from related models, such as the sequential search model (Weitzman 1979), the multiarmed bandit model (Gittins 1979, Brezzi and Lai 2002), and the model of consumer search with learning (Rothschild 1974, Koulayev 2013, De los Santos et al. 2017). Because it allows consumers to search the same option multiple times before a single purchase decision, it differs from the sequential search and the multiarmed bandit models. In addition, the fact that consumers learn about their match values rather than the distribution of rewards in the market distinguishes it from existing models of search with learning following Rothschild (1974). Our approach provides a general framework to study consumer engagement with a product through search, being able to also capture decisions, such as revisits to a previously searched product to resolve further uncertainty.

The empirical setting in which we estimate the proposed model is consumer search for restaurants on an Asian review website. On this website, consumers start their search by visiting the homepage and specifying a query, that is either searching for a restaurant by typing in a keyword or using one of the menu options, such as cuisine type or location. In response to this query, consumers see an ordered list of restaurants (the list page), which contains some information about each option, such as average reviews and price. Consumers can then search a restaurant to obtain additional information by clicking on it. In this case, they navigate to a second screen dedicated to that restaurant (the restaurant page). Finally, a consumer can decide to visit the restaurant (offline) when her search ceases, equivalent to her making a purchase decision. We have data on all these restaurant characteristics and the choices consumers make in response to the information observed.

These data provide insights on consumers searching on both the intensive and the extensive margins. More precisely, we have data on which products consumers clicked/searched (extensive margin), how much time they spent searching each product (intensive margin), and which products they purchased, if any. Using these data, we document that search duration is considerable, even when consumers search few restaurants. In addition, we find that search duration is related to purchases, so that restaurants that consumers spend more time searching are also the ones they purchase. For a given restaurant, the more information is displayed upon search, the longer is the search duration. This suggests that duration provides a benefit in the form of information discovered through search that might influence purchase decisions, while at the same time, imposing a cost that prevents consumers from fully revealing all uncertainty about all options. That is, search duration is a choice made in addition to search and purchase decisions. This finding makes the empirical setting favorable for estimating a model that endogenizes the consumer's search duration decision.

To estimate the model, we first adapt it to the empirical setting. More precisely, we assume consumers search to decide whether to purchase from a restaurant. The utility of a restaurant is influenced by consumers' preferences for restaurant characteristics observed on the list page before search, and their beliefs about product match values given information observed through search up to that point. Consumer beliefs are influenced by their prior uncertainty, as well as by the restaurant page characteristics observed through search. Search is costly but provides (noisy) signals about the restaurant's match value that are a function of the restaurant page information observed. Consumers then use these signals to update their beliefs about restaurant match values in a Bayesian fashion. At each stage, consumers decide whether to continue spending time on that restaurant's page; return to the list page and click a different restaurant; or make a purchase decision. The more time spent on the restaurant's page, the more information consumers can gather.

We estimate our model and quantify consumer preferences, search costs, and prior beliefs parameters. We find average search costs of \$0.07 per minute, generally lower than estimates reported in previous work without search duration. We also find that prior beliefs play an important role in guiding consumers' search. In particular, we find that consumers start their search with relatively high prior uncertainty, rationalizing their choice to spend a considerable amount of time searching each restaurant. We account for consumer heterogeneity in the model using a latent class approach and find evidence of two segments of consumers: the first segment is relatively less price sensitive and begins search with higher prior uncertainty and has higher search costs than the second segment. This suggests that the first segment of consumers searches few options but for a long time, while the second segment searches many options but spends a relatively shorter amount of time searching. Without information on search duration, such differences in behavior would be attributed only to differences in preferences and search costs, likely biasing these estimates.

Our results highlight a number of benefits of modeling search duration. First, the model may allow better recovery of consumer preferences from data. More precisely, a distinguishing feature of our model is that it allows us to estimate consumer preferences for not only characteristics observed before search but also information observed after search, because this information affects the signals consumers obtain through search. Our results may thus be of interest to managers allowing better predictions of conversion rates or repeat purchase probabilities.

Second, our model allows us to estimate consumer prior beliefs in addition to their preference and search costs. Consumers start their search with different amounts of information and thus beliefs, and this may affect which products they search and what they buy. However, previous work ignores this effect. In contrast, by combining a model of search with a learning model, we are able to additionally measure the effect of prior beliefs on search and purchase decisions. Capturing consumers' awareness prior to search may allow managers to target consumers based on their familiarity with the product or their stage in the purchase funnel.

Third, another feature of the model is that it leads to search cost estimates measured in units of time rather than per product. We believe this feature makes our approach desirable to researchers seeking to compare search cost estimates across product categories. In addition, by measuring the cost of gathering information in units of time, our approach opens up the possibility of using search models to quantify a consumer's opportunity cost of time, a more fundamental consumer primitive. Modeling search duration also allows us to better estimate search costs. More precisely, without information on search duration, the fact that a consumer searches fewer options than another would suggest that her search costs are higher, ceteris paribus. However, with information on search duration, the fact that a consumer searches few options does not necessarily suggest large search cost if she spends a long time searching.

Fourth, modeling search duration allows us to address new managerially relevant questions related to the amount of information companies should provide consumers upon search. Many companies, such as search intermediaries or online platforms, need to decide how much information to provide consumers about each available product. Providing too much information may prevent consumers from searching enough products, while providing too little information may prevent them from acquiring the necessary information to make a purchase decision. Our model of sequential search, which endogenizes the intensive and the extensive margins of search, is well suited to help companies resolve this a trade-off. To illustrate, we perform two counterfactuals related to the amount of information to reveal to consumers. First, we ask whether the review website in our data application would benefit from increasing the amount of information it is providing to consumers, or whether it is already providing too much information.[1] Given our estimated parameters, we find that providing more information to consumers is beneficial (compared with the default information provided by the site), increasing the consumer's utility from a searched option, and increasing revenues. Second, we ask whether the amount of information displayed to consumers by the review site upon search should be taken into account when the company ranks/orders products. Previous work ignores this possibility, lacking data on the information revealed to consumers through search (Ghose et al. 2012, 2014; Chen and Yao 2016; Ursu 2018). However, if the intensive margin of search plays a role in the search process, this information should not be ignored by ranking algorithms. Indeed, we find that a ranking accounting for the amount of information displayed would increase the number of restaurants searched, search duration and revenues, overall benefiting both the company and the consumer.

The rest of the paper is organized as follows. The next section discusses relevant prior work. Section 3 introduces our model and describes consumers' optimal search rules. In Section 4, we discuss the specific empirical context of our analysis, the data we employ, and provide descriptive statistics on search duration. Section 5 describes our empirical model and estimation procedure, as well as its identification. In Section 6, we describe our estimation results, while in Section 7, we provide managerial implications using a counterfactual. The last section concludes.

2. Literature

This paper connects two literature strands: consumer search and Bayesian learning. The consumer search literature generally follows either Stigler's (1961) theoretical model of simultaneous search or Weitzman's (1979) sequential search theory. In these models, consumers know the distribution of rewards (e.g., price, match values), but search to reveal the reward of a specific product. Search reveals all uncertainty about the searched product. Both papers derive optimal search rules for consumers. In the case of simultaneous search, consumers search the set of products providing the maximum expected reward net of search costs. In the case of sequential search, the optimal search rules are characterized by a reservation policy: consumers search options in order of their reservation values (an index describing the hypothetical observed reward that would make the consumer indifferent between searching and stopping), stop when no alternative has a reservation value greater than the realized reward of the searched alternatives, and buy if the product with the highest realized reward is greater than the value of not purchasing. In our model, search is sequential, but the consumer can search the same option multiple times, leading to different optimal search rules than those in Weitzman (1979).

The empirical search literature quantifies the impact of search frictions on search and purchase decisions (Hong and Shum 2006; Moraga-Gonzalez and Wildenbeest 2008; Kim et al. 2010, 2017; Seiler 2013; Honka 2014; Koulayev 2014; Moraga-Gonzalez et al. 2015; Chen and Yao 2016; Honka and Chintagunta 2016; Ghose et al. 2019) by estimating consumer preferences and their search cost parameters. Ours is also an empirical search paper. However, it differs from this literature because in our model consumer information is not revealed fully in one search action, but rather consumers update their prior beliefs on product match values in a Bayesian fashion through search. As such, our paper is related to the literature on Bayesian learning in dynamic brand choice models. Erdem and Keane (1996), Ackerberg (2003), and Erdem et al. (2008), among others, consider the signaling effect on product quality of a host of factors, such advertising content and frequency, experience and prices. Researchers estimate consumer preferences jointly with their prior beliefs about products. Our model also differs from this work in that we consider learning through search prior to a purchase decision, rather than through repeat purchases. By combining the two strands of the literature on consumer search and Bayesian learning, we develop a model that allows consumers to learn their match value while searching sequentially for product information. With this model, we are able to quantify a richer set of factors influencing consumer choices that combine those of these two literature strands. More precisely, we estimate consumer preferences, search costs and prior beliefs, which provides new insights relating three stages of the consumer decision making journey: search, awareness, and choice.

We model search duration as the consumer's decision to search the same option multiple times, so naturally our model is related to work on multiarmed bandit problems (Gittins 1979, Brezzi and Lai 2002). In these models, consumers look to maximize the sum of rewards from sequentially sampling options, including sampling the same option multiple times. Such models are suitable to study repeat purchase occasions, as in Lin et al. (2014). In contrast, in our model consumers maximize the rewards from a single option chosen after sequentially searching for information about available options. As a result, we model repeated search decisions (e.g., time spent searching, revisits) and a single purchase decision.

Our work is closely related to papers that model search with learning. In Table 1, we provide a quick overview of papers in this literature and show how our paper fits in. Papers are ordered chronologically and by the type of search learning assumed: gathering information on product attributes, learning about the market distribution of the product characteristic consumers search for (e.g., price), or learning about consumers' match values. We also differentiate papers by theoretical versus empirical work, by whether they model search as simultaneous or sequential, by whether they derive or use optimal search rules to describe consumer behavior, by the type of distribution assumed for the beliefs of consumers, and, finally, by the number of products considered.

The first group of papers models search for product attributes. In these models, consumers have some basic product information and decide sequentially whether to obtain additional information on other product features. Branco et al. (2012, 2016) consider the case of one product and study how the optimal stopping rule (there is no selection rule in this case, because the model contains just one product) depends on model parameters, such as search costs.

Table 1. Literature on Search with Learning

	Learning	Theory/ empirical	Simultaneous/ sequential	Optimal search rules	Distribution of beliefs	Number of products
Branco et al. 2012	Attributes	Theory	Sequential	Yes[a]	Symmetric	1
Branco et al. 2016	Attributes	Theory	Sequential	Yes[a]	Symmetric	1
Ke et al. 2016	Attributes	Theory	Sequential	Yes	Symmetric	≥ 2
Gardete and Antill 2019	Attributes	Empirical	Sequential	Yes	Empirical	N
Rothschild 1974	Market	Theory	Sequential	Yes	General	N
Koulayev 2013	Market	Empirical	Sequential	Yes	Dirichlet	N
De los Santos et al. 2017	Market	Empirical	Sequential	Yes	Dirichlet	N
Hu et al. 2019	Market	Empirical	NA	Yes	Dirichlet	N
Chick and Frazier 2012	Match	Theory	Sequential	Yes	Normal	N
Dukes and Liu 2015	Match	Theory	Simultaneous	Yes	Extreme value	N
Ma 2016	Match	Empirical	Sequential	No	Normal	N
Ke and Villas-Boas 2019	Match	Theory	Sequential	Yes	Two point	≥ 2
Our paper	**Match**	**Empirical**	**Sequential**	**Yes**	**Normal**	**N**

Notes. Boldface text emphasizes how this current paper differs from the literature. NA, not applicable.
[a] The selection rule does not apply in this case since the model considers only one product.

Ke et al. (2016) focus on two products that they later extend to more products and derive optimal search rules when attributes are independent and search informativeness is constant. Most recently, Gardete and Antill (2019) propose a model in which consumers can search to learn product attributes with possibly correlated characteristics. Consumers can search the same option multiple times, but only up to the number of unknown features of the product. That is, after searching n times for its n features, the consumer reveals all uncertainty about a product. In contrast to this set of papers, we do not observe what characteristics consumers reveal through search, but only observe the time they spend searching, which we model as search to learn consumers' match value for the product. Also, in our model search allows the consumer to update her beliefs in a Bayesian fashion, lowering her uncertainty while searching, but never reducing it to zero. Finally, modeling learning allows us to estimate consumers' prior beliefs about products, in addition to their preference and search costs.

In the second group of papers, Koulayev (2013) and De los Santos et al. (2017) follow the theoretical framework of Rothschild (1974) and assume consumers search for the highest reward (i.e., the lowest price), while learning about the market distribution of rewards. They form beliefs about this distribution (both assume Dirichlet priors), search to reveal information about one company's product and update their beliefs about the distribution using Bayes' rule, which they use to decide whether to search another product. In this setting, the optimal search rule is also an index/reservation policy as in the case of search without learning (e.g., in Weitzman 1979), except that here reservation utilities are nonincreasing over time, so consumers are more likely to accept an offer over time in the model with learning than in the one without. In contrast to our setting, here consumers will not search the same product more than once (except in order to return and accept a previous offer). Also, in our model consumers learn about their individual match values (instead of the distribution of rewards across all products in the market), allowing them to decide when it is optimal to switch from learning about one product to learning about another. Recently, Hu et al. (2019) model the decisions of consumers who observe Groupon deals daily, decide whether to click, learn about the distribution of deals if they click, and make purchase decisions. This model also differs from ours in several respects: search is assumed passive (deals arrive every day, rather than consumers seeking out options to search), and consumers learn about the market distribution of rewards rather than their match value. As a result, the problem that consumers are solving in these settings is fundamentally different from ours, leading to different optimal search rules and different consumer behavior.

Most closely related to our work, papers in the third group model learning for match values. Dukes and Liu (2015) investigate the strategic interplay between search intermediaries, companies and consumers, when consumers decide optimally both the extensive and the intensive margins of their search. Under simultaneous search and assuming consumers choose the same intensive margin of search for all searched products, they show how search costs, the intermediary's search engine design, and firm pricing decisions affect the amount of search in equilibrium. In our paper, we focus on the demand side of the model and estimate a sequential search model using consumer optimal search rules. Ma (2016) embeds an Erdem and Keane (1996) like framework into a sequential search model, where consumers can learn about product quality by choosing whether to observe signals from different types of product reviews. However, the paper does not use/derive the optimal search rules for the full set of decisions made by consumers. Finally, Ke and Villas-Boas (2019) focus on the case of two products (which they later extend to three products) and derive the optimal sequential search strategy when rewards are drawn from a two-point distribution. In contrast, we follow Chick and Frazier (2012), who derive optimal search rules when consumers search sequentially among any number of alternatives and hold normally distributed beliefs. In addition, we take this model to data and propose an estimation strategy for it.

A number of other papers are also related to our work. Jindal and Aribarg (2018) study the impact of prior beliefs on search in a laboratory setting where they elicit consumers' prior beliefs about the price distribution before search. They find that assuming consumers know the true distribution of prices can bias search cost estimates. Although our methods differ (we recover consumer prior beliefs from a Bayesian learning model of search that imposes structure on the way in which consumers learn and make search and purchase decisions), we also highlight the importance of understanding consumer priors and their effect on search decisions. Two recent papers provide data patterns on search duration. More precisely, De los Santos (2017) finds that, in searching for books, duration is affected both by previous consumer choices (e.g., past bookstores visited) and their demographics, as older consumers with lower education or income levels tend to spend more time searching. This shows that consumers' opportunity cost of time is an important factor in the decision to search on the intensive margin. Seiler and Pinna (2017), without modeling search on the extensive margin, measure the change in price paid from spending an additional minute searching in a supermarket setting and find a benefit of $2.10 per minute. Both of these papers provide insights on the importance of search duration hinting at its dual effects: providing a benefit but at a measurable cost. This suggests the need to quantify these two effects using a model that endogenizes the search duration decision, which is the focus of this paper.

3. Model

3.1. Consumer Problem

Consider a consumer $i \in \{1, \ldots, N\}$ who seeks to purchase an alternative $j \in \{1, \ldots, J\}$ or choose the outside option (denoted by $j = 0$). The expected utility of the outside option is known, but the consumer faces uncertainty about the J options. To (partially) resolve this uncertainty, the consumer can search for information before making a purchase decision, which involves paying a cost per search, $c_{ij} > 0$. The consumer's goal is to maximize her expected utility net of total search costs from the best option she will choose to purchase when search ceases.

Searching an alternative once does not resolve all the consumer's uncertainty. To obtain further information, the consumer can search the same option in multiple time periods, where time is discrete and indexed by $t = 1, \ldots, T$. To model search duration, we will interpret time spent searching an option as the consumer's choice to search the same option multiple times. Although we focus on search duration, this same approach can be used to model revisits of previously searched options, as we demonstrate below (see Figure 2).

Each time period, the consumer decides whether to continue searching, in which case she chooses a product to search, or whether to stop, in which case, she decides which product to purchase, if any. We model the consumer's utility from purchasing product j at time t as

$$u_{ijt} = \mu_{ijt} + \epsilon_{ij}, \tag{1}$$

where μ_{ijt} is the consumer's perceived match value with product j in period t, and $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$ is an idiosyncratic shock, unobserved by the researcher, but known to the consumer before search.[2]

The consumer is uncertain about the true match value of each of the J alternatives, which is normally distributed with unknown mean μ_{ij} and known variance σ_j^2. She holds beliefs about her match value, which she updates in a Bayesian fashion using information gained through search. More precisely, the consumer can search to learn the unknown mean by obtaining (unbiased) signals on j at t given by

$$s_{ijt} \sim N\left(\mu_{ij}, \sigma_j^2\right), \tag{2}$$

at a cost of c_{ij} per search. Because draws are independent, the consumer does not learn about the match value of one product by searching another. Initially, the consumer's prior beliefs are summarized by

$$N\left(\mu_{ij0}, \sigma_j^2 / n_{ij0}\right), \tag{3}$$

where μ_{ij0} is the prior mean and n_{ij0} gives the implied number of samples drawn to form the prior belief. We follow Chick and Frazier (2012) to write the prior variance as a ratio of the true variance σ_j^2 and n_{ij0}. This allows us to use their results to characterize the optimal search rules of the consumer, as we do in the next section. Also, this approach simplifies the exposition of the model because only the ratio of prior and signal variances can be recovered through estimation (for more details on the identification of the empirical model, see Section 5.3).

After searching j at t, the consumer's posterior belief about her match value is formed using Bayes' rule and equals

$$N\left(\mu_{ijt+1}, \sigma_j^2 / n_{ijt+1}\right), \tag{4}$$

where

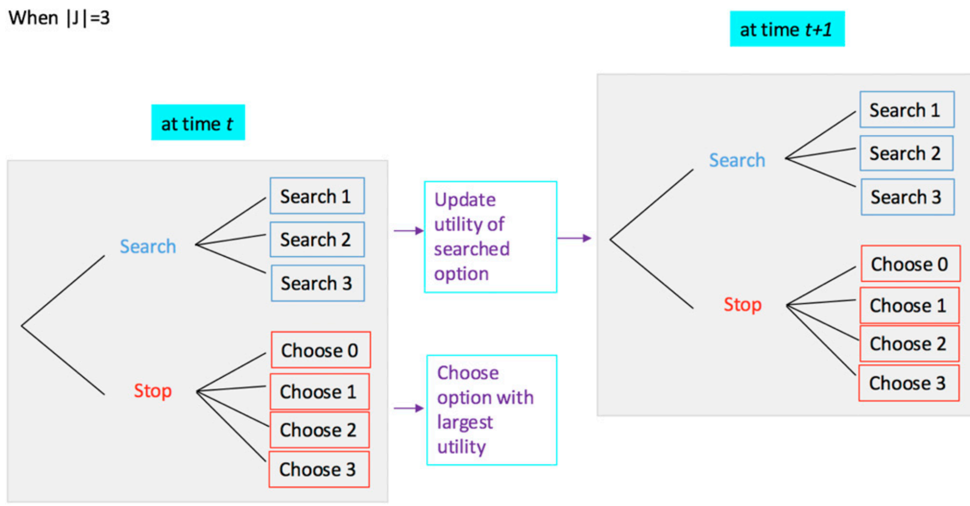
$$\begin{aligned} \mu_{ijt+1} &= \frac{n_{ijt}\mu_{ijt} + s_{ijt}}{n_{ijt+1}} \\ n_{ijt+1} &= n_{ijt} + 1, \end{aligned} \tag{5}$$

while for $k \neq j$, $\mu_{ikt+1} = \mu_{ikt}$ and $n_{ikt+1} = n_{ikt}$, that is, options that are not searched are not updated.

In contrast to the J alternatives' unknown mean match value, the outside option of not purchasing has a known expected utility, which we normalize to zero, that is $u_{i0} = \epsilon_{i0}$. The interpretation of this assumption is that the consumer chooses between one of the J alternatives or rejects all of them, obtaining zero mean utility.

Figure 1 illustrates the consumer's sequential search procedure. Suppose the consumer has three options to choose from. In a given time period t, the consumer can either continue or stop searching. If she continues searching, then she must choose the option to search next. If instead she decides to stop searching, then she chooses whether to purchase one of the three options or choose the outside option (option 0) of not purchasing. At any stage in the search process, the consumer uses all data observed thus far to make a decision. For example, at time t, if she chooses to search option 2, then she observes a signal about this product, which she uses to update her belief about her posterior utility of 2. Her beliefs about the other two options stay the same, because the consumer did not observe any new information about these. Then, in the next period, she again can choose to continue searching or to stop. Importantly, she can choose to search any of the three options available, including the previously searched option 2. The possibility of searching the same option as before is what distinguishes

Figure 1. (Color online) Model Illustration: Sequential Search



this model from previous search models in the literature that assume all the uncertainty of the consumer about a product is resolved in a single search action.

As mentioned previously, this same model also can be used to model revisits of previously searched options. To see why this is the case, consider Figure 2. Suppose, for example, that the consumer searches option 2 in period t and switches to searching option 1 in period $t+1$. The decision to search option 2 again in the next period, which defines a revisit, can be accommodated by our model, because searching an option does not reveal all uncertainty about it, so previously searched options can be searched again.

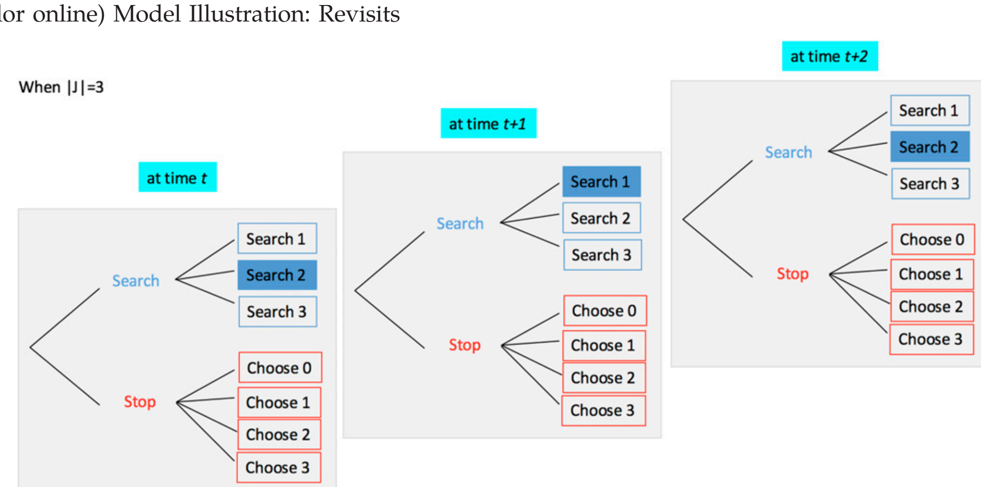
3.2. Optimal Search

At a given point during search, the consumer must decide whether to continue searching, and if so, which alternative to sample next. Upon stopping her search, she must decide whether to purchase. To determine how consumers should make such decisions, we follow Chick and Frazier (2012), who describe the optimal search policy in this setting. Let the state of information about option j at t for a given consumer i be given by $\Theta_{jt} = (\mu_{jt}, n_{jt})$ and the state of the system at t be $\vec{\Theta}_t = (\Theta_{0t}, \Theta_{1t}, \ldots, \Theta_{Jt})$. The optimal policy is one that determines which j to search/purchase at each t given $\vec{\Theta}_{jt}$ in order to maximize the expected utility from the outcome chosen once search terminates net of total search costs. Chick and Frazier (2012) frame this problem using dynamic programming and show that the optimal policy is one that attains the maximum of the following Bellman recursion problem

$$V\left(\vec{\Theta}_t\right) = \max\left\{\max_{j=1,\ldots,J} E\left(-c_j + V\left(\vec{\Theta}_{t+1}\middle|\vec{\Theta}_t\right)\right), \max_{j=0,1,\ldots,J} E\left(u_{jt}\middle|\vec{\Theta}_t\right)\right\}. \tag{6}$$

Chick and Frazier (2012) solve for the optimal policy in two steps. First, after proving the existence of an upper bound on the total number of searches a consumer will make, they consider the case with one alternative ($J = 1$), one outside option, and normally

Figure 2. (Color online) Model Illustration: Revisits



distributed rewards with unknown means and known variances. This problem can be solved using the Bellman recursion above given the upper bound on the total number of searches. However, the solution depends on parameters of the model, and it would have to be recomputed when these change. Thus, instead of this approach, they choose to transform the discrete-time problem to continuous-time and use diffusion approximation to describe the solution (similar to approaches used for multiarmed bandit problems, e.g., Chernoff and Ray 1965, Lai 1987, Brezzi and Lai 2002, Chick and Gans 2009). This approach allows them to write the problem in a "standardized form," so that by solving one optimal stopping problem, they can solve it for any variation in model parameters. Their solution determines a continuation set, within which continuing to search is optimal, and outside of which it is optimal for the consumer to stop searching and choose either the alternative or the outside option, whichever is better. More precisely, they derive a function $b(h)$ (defined in Equation (10)) and show that for values of h in the interval $(0.08, 6300)$, it can be used to provide a good approximation to the optimal continuation set. Chick and Frazier (2012) can draw this conclusion given that they know the optimal solution for the case of one alternative and can compare it to the proposed approximation.

Second, they use results from the case of one alternative to provide approximations to the solution for the case of $J > 1$. We note that the search rules may not be optimal when $J > 1$, because they are derived from an approximation to the dynamic programming problem. However, Chick and Frazier (2012) show that these perform very well in numerical simulations when compared with a host of other rules proposed in the literature, such as the knowledge gradient policy. In addition, they are easier to implement than solving the dynamic programming problem using Bellman recursion. The parameters we estimate in Section 6 and in the simulation exercise in Section 5.4 (ranging from 7.04 to 61.31 in estimation, and from 0.20 to 4.85 in simulation), fall well within the ranges $(0.08, 6, 300)$ tested by Chick and Frazier (2012), so we conclude that using the search rules derived in their paper will provide good approximations to the optimal search rules. For additional details on the method used by Chick and Frazier (2012), see Online Appendix A.

The optimal policy for the case of $J > 1$ is characterized by three search rules. We follow the search rules based on the stopping boundary that Chick and Frazier (2012) derive:[3]

1. **Stopping Rule**: Continue to search at t if and only if $\exists\, j \in (1, \ldots, J)$ such that its posterior mean utility u_{ijt} lies within the *continuation set*, that is, $u_{ijt} \in (\max_{k \neq j} u_{ikt} \pm M_{ijt}(c_{ij}, \sigma_j, n_{ijt}))$, for $k \in (0, 1, \ldots, J)$, where M_{ijt} is the boundary of search, a function of search costs and product uncertainty that we define in Equation (9). This condition can be rewritten as follows: search will continue at t if and only if $\exists\, j \in (1, \ldots, J)$ such that

$$M_{ijt}(c_{ij}, \sigma_j, n_{ijt}) > \Delta_{ijt}, \tag{7}$$

where $\Delta_{ijt} = |u_{ijt} - \max_{k \neq j} u_{ikt}|$ for $k \in (0, 1, \ldots, J)$.

2. **Selection Rule**: While the stopping rule is not satisfied, choose to sample the alternative $j \in (1, \ldots, J)$ such that

$$\arg\max_j \frac{M_{ijt}(c_{ij}, \sigma_j, n_{ijt}) - \Delta_{ijt}}{c_{ij}^{1/3} \sigma_j^{2/3}}. \tag{8}$$

3. **Choice Rule**: Conditional on stopping, choose the alternative $j \in (0, 1, \ldots, J)$ with the largest posterior expected utility.

The optimal search rules can be understood as follows. The stopping rule dictates that the consumer will continue searching if at least one alternative falls within the continuation set, that is if comparing its posterior mean utility and the maximum posterior mean utility of all other alternatives (and the outside option) is smaller than the boundary of search. Thus, all alternatives that fall within the continuation set are potential candidates for further search, while those outside the continuation set will not be searched at t (although they might be searched at a different time). This implies that both options with very large and those with very small posterior utility might not be candidates for search in a given period. This is true, because consumers are uncertain about the true match value of a product and are only willing to pay to search if the expected increase in utility together with the reduction in uncertainty is sufficient. The selection rule says that if the consumer finds it optimal to search at t, then she should search the option that is furthest inside the continuation set as measured in standardized coordinates. This rule translates to the consumer choosing to search the option within the continuation set that has relatively lower search costs and higher posterior mean utility. Finally, the choice rule, a familiar decision rule in marketing, says it is optimal for the consumer to pick the product with the largest posterior utility once search stops. Note that the model allows for the possibility of consumers choosing an option they did not search.

To complete the description of the optimal search rules, we must describe the boundary of search, $M_{ijt}(\cdot)$. The specific functional form for the boundary of search comes from solving the dynamic programming problem in Equation (6) using diffusion approximation. Chick and Frazier (2012) show that it is given by

$$M_{ijt}\left(c_{ij}, \sigma_j, n_{ijt}\right) = c_{ij}^{1/3}\sigma_j^{2/3} b\left(\sigma_j^{2/3} \Big/ \left(c_{ij}^{2/3} n_{ijt}\right)\right), \tag{9}$$

where $b(h)$ can be approximated by[4]

$$\hat{b}(h) = \begin{cases} 0.233h^2, & \text{if } h \le 1 \\ 0.00537h^4 - 0.06906h^3 \\ \quad + 0.3167h^2 - 0.02326h, & \text{if } 1 < h \le 3 \\ 0.705h^{1/2}\ln(h), & \text{if } 3 < h \le 40 \\ (3h\log(h) - \ln(8\pi) \\ \quad - 2/\ln(h) - 170)^{1/2}, & \text{if } h > 40. \end{cases} \tag{10}$$

This approximation for $b(\cdot)$ is similar to results in the related multiarmed bandit problem (Gittins 1989, Brezzi and Lai 2002).

The boundary of search is nonnegative, because $\hat{b}(\cdot)$ is nonnegative. It is straightforward to derive the relation between $M_{ijt}(\cdot)$ and its arguments. We illustrate these relations in Figure 3. As can be seen in this figure or derived more formally from Equation (9), the boundary of search is decreasing in search costs c_{ij} and the number of samples n_{ijt} drawn, and increasing in the signal variance, σ_j^2. As a result, $M_{ijt}(\cdot)$ has intuitive properties: higher search costs and lower prior uncertainty both lead to a lower boundary of search and thus a lower likelihood of search.

3.3. Relation to Other Approaches

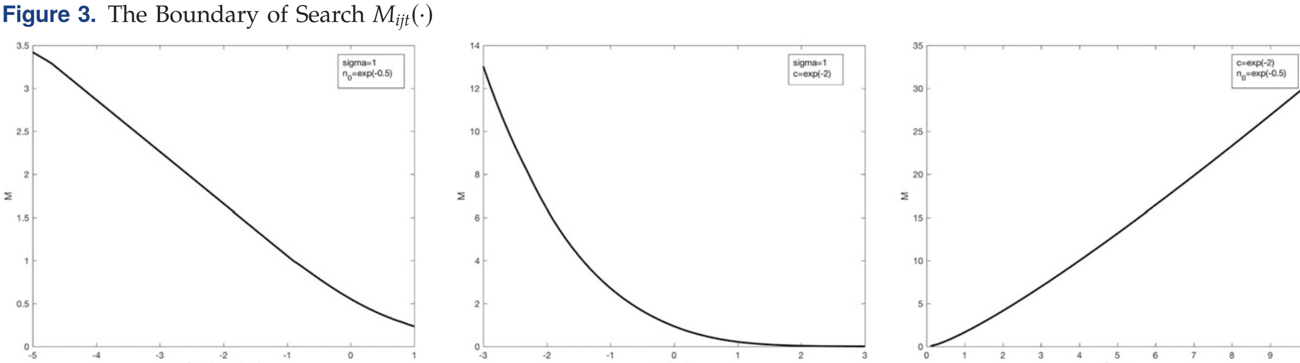
In this section, we compare the model presented in Section 3 to the sequential search model of Weitzman (1979), which is commonly used in marketing, and to the more general framework of multiarmed bandits. Although these models are related, there are important differences distinguishing them that we highlight here.

The model presented in this paper assumes consumers want to purchase a product and are initially unsure of their match with the product. However, they can search before deciding whether to purchase, which is costly, but reveals informative signals about their match value. The goal of a consumer is to maximize her expected utility net of total search costs from the best option she will choose when search ceases.

In Weitzman's (1979) search problem, the consumer faces a set of options and can sequentially sample each. Searching an option reveals all uncertainty about it and the consumer focuses on deciding whether to continue searching any of the unsearched options or stop and choose one of the searched options. Optimal search is characterized by an index, known as the reservation utility of an option, capturing all relevant information on the expected utility and cost of searching the option. The consumer will terminate search when the maximum utility observed so far exceeds the reservation utility of the next best option and will continue searching otherwise. However, because all uncertainty about an option is revealed after search, this model cannot be used to study the consumer's decision to search the same option multiple times (e.g., spend time searching, revisit a previously searched option), which is the goal of our paper.

In contrast to Weitzman's (1979) sequential search problem which describes the case where consumers cannot search the same option multiple times, more general multiarmed bandit problems deal with the case where the same option is sampled multiple times. In such problems, the consumer can observe rewards from a number of alternatives, described by different reward distributions. By sampling an option, she learns about the distribution of that option and can continue sampling from all options, including the ones already sampled. There is an implicit trade-off the consumer is facing between exploiting her knowledge from the sampled options or exploring potentially less appealing options currently in order to learn about their reward distribution and make better choices in the future. The goal of the consumer is to maximize the (discounted) sum of rewards. The optimal policy is characterized in Gittins and Jones (1974) and Gittins (1979) in terms of an index rule that dictates the consumer should choose in each time

Figure 3. The Boundary of Search $M_{ijt}(\cdot)$



period the option with the largest index. The Gittins index resembles the role of the reservation utility in the Weitzman's (1979) sequential search model. This model is well suited to study repeated purchase decisions (as in Lin et al. 2014). However, in this model, the consumer accumulates rewards after each period, so it is not well suited for the problem in this paper, where the consumer's goal is to maximize the single utility net of total search costs from the option chosen after search ceases. A natural extension of the multiarmed bandit model to account for multiple searches before a single purchase is the model by Chick and Frazier (2012), which is the framework we adopt here.

In sum, in order to study the time consumers choose to spend searching an option, we need a model that allows them to search the same option multiple times with each search being costly. The model presented in this paper provides exactly such a framework. In the next section, we discuss the data we will use to estimate this model.

4. Data

4.1. Search Process

The specific empirical context of our analysis is consumer search for restaurants on an Asian review website. At the time of our data collection, this website provided review information for many products and services, but mainly focused on restaurants (similar to Yelp). We start by describing consumers' three step search process on this website, as illustrated by Figure 4.[5]

Consumers start their search by visiting the homepage of the website. Here they can find a restaurant either by typing in a keyword in the search bar at the top, or by searching by location, restaurant features, or another menu option (step 1). We refer to these actions as "specifying a query." In response to a query, consumers see an ordered list of restaurants,[6] typically divided into pages with 10 results per page. The consumer can make multiple queries. If these queries are less than one hour apart, we will interpret them as belonging to the same session, consistent with previous work (Wu et al. 2015). The list page contains some information about the displayed restaurants, such as the name, location, average rating and average price. The consumer can then search a restaurant to obtain additional information by clicking on it (step 2). In this case, they navigate to a second screen reserved for that restaurant, which we refer to as the restaurant page. Here they can see photos, additional restaurant information, as well as previous consumer reviews ordered by posting date. Given the amount of information on this page, consumers decide how much time to spend on a restaurant page, whether to return to the list and make another search, or whether to purchase (step 3). We interpret clicking on the list page as search on the extensive margin, while spending time on the restaurant page as search on the intensive margin. Finally, the consumer can decide to visit the restaurant (offline) when her search ceases. In what follows, we call this visit the consumer's purchase decision.

4.2. Data Sources

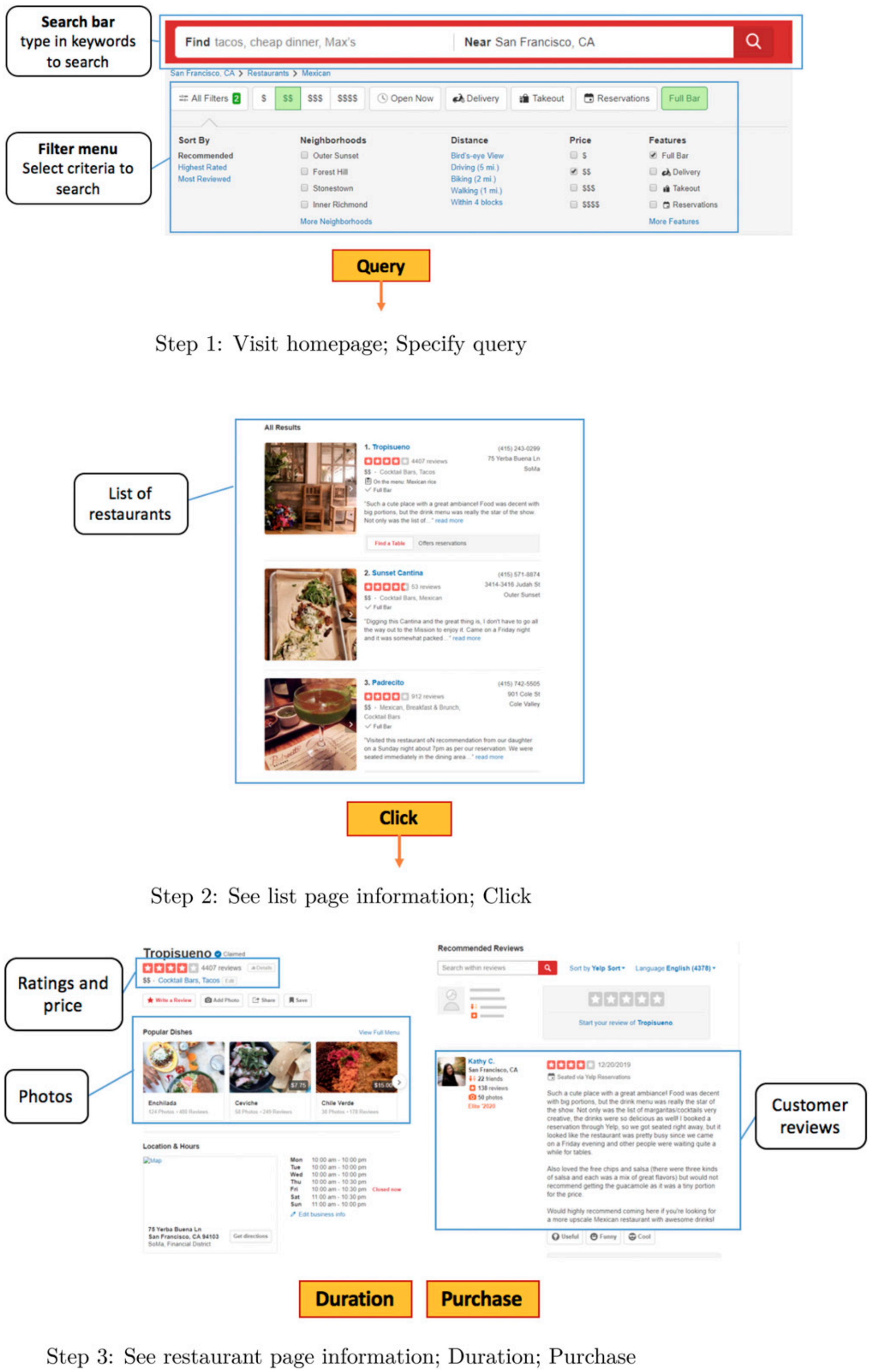
We use two main data sources in this paper. One data source is obtained from the Asian review website. This has three components. First is a click stream data set containing searches consumers made on the site from December 2007 to March 2008. Importantly, these data contain information on the date and time of the click, which allows us to compute the duration of a click, using differences in time stamps. One concern with using time stamps to measure duration is measurement error. More precisely, we observe when consumers clicked on the restaurant page and when they clicked to go back to the list page or another page. However, we do not observe exactly what they did in this time interval, that is whether they spent time reading about the restaurant or whether they were engaged in another activity. Although we cannot fully alleviate this concern, we do two things to partially address it. First, we collapse durations above 10 minutes, because they are more likely to include activities not related to restaurant viewing. Second, we use the duration variable measured by comScore to cross-check the time spent on a click on a similar website (Yelp). As we show in the section below, we find very similar duration measures in the comScore data as in our own.

In general, having time stamp information would allow us to obtain duration information for all clicks but the last click made by the consumer (duration would be truncated). However, the data include not only clicks made on restaurants but also clicks to the homepage of the website, clicks on the consumer's profile on the site, other member's profiles clicks, clicks to chat pages, etc. Thus, we are able to directly observe duration information for 79% of clicks and 40% of last clicks.

The second data component describes restaurant page characteristics of the clicked restaurants for the period April 2003 to March 2008.

Third, we have individual level transactions for the period May 2005 to March 2008 of consumers who have a loyalty card distributed by the website from restaurants which collaborate with it. By using the loyalty card at the restaurant, consumers obtain a 10%-30% discount at collaborating restaurants. Note that consumers' use of this loyalty card allows us to link online queries to offline transactions for (possibly) only a subset of purchases, and thus our transaction

Figure 4. (Color online) Search Process Illustration



data are truncated. However, given the significant discount provided by the loyalty program, we anticipate this truncation to only have a minor impact on our data collection efforts. To further minimize the impact of truncation, we will focus our analysis on consumers who make a purchase. Although we limit the analysis to converting consumers, we observe both converting and nonconverting sessions, where we call a nonconverting session one in which more than 75% of the clicked restaurants participate in the loyalty program.

Because we are interested in modeling consumer search, we need to observe not only which restaurants consumers clicked but also those they did not search, information that is not included in the first data source. Thus, to augment the data on the restaurants clicked, we use a second data source, which comes from an Internet archiving website called "Wayback Machine" (WBM).[7] Using the keywords that consumers searched and the time of search, we retrieve from the WBM the list of restaurants that consumers likely saw as a response to their query. We require that the keywords consumers searched should be exactly matched with the ones save on WBM. However, because the time of search usually cannot be exactly matched, we retrieve the closest time that the keyword search was saved. Given that data on WBM becomes more sparse going further back in time, we are able to match 68% of queries, which we will use in the analysis.

4.3. Final Data Sample

In our final data sample, there are 343,270 observations, where an observation is a restaurant displayed to consumers in response to their query. We observe 5,465 consumers searching across a total of 17,852 sessions and 34,912 queries and making 50,439 clicks and 7,538 transactions (21.59% of queries end in a transaction). Revisits, defined as multiple nonconsecutive clicks on the same restaurant, are prevalent in the data: 23% of queries and 30% of sessions contain at least one revisited restaurant.[8] There are 10,632 restaurants in the data, and, in Table 2, we summarize the average restaurant characteristics we observe.

The list page includes information on the rating of the restaurant (weighted sum of taste, ambience and service measures),[9] the average price of a meal (which we transformed to dollars), a promotion indicator, the number of reviews of the restaurant (measured in thousands), as well as its position in the list.[10] As can be seen, clicked, purchased or restaurants on which consumers spent more time generally have a higher rating and lower prices. If the consumer clicked on a restaurant on the list page, then we observe additional information as contained on the restaurant page, such as the number of photos, the length of the introduction posted by the owner of the restaurant (measured in words), as well as the individual consumer reviews posted, which we summarize using the average review length (measured in thousands of words). In general, the more information is displayed on the restaurant page, the longer consumers spend on the restaurant page. We also find that on average queries are made by consumers who registered with the website approximately two years in advance (mean = 681.62 days, standard deviation = 418.24 days). We will refer to this variable as the consumer's experience with the website. Finally, we find that on average a transaction happens less than one week after the query (mean = 6.21 days; standard deviation = 12.79 days).

4.4. Data Patterns on Search Duration

In this section, we show how consumers search on the intensive margin using data on the time they spend searching restaurants. More precisely, we provide evidence on how much time consumers search, on what affects search duration, and on the effect of duration on purchase decisions.

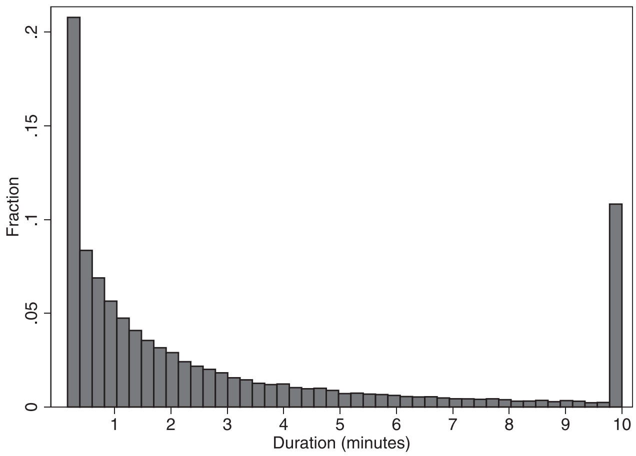
4.4.1. How Much Time Do Consumers Spend Searching?

We find that consumer search on the intensive margin is considerable: the average (median) consumer spends 3.47 (2.45) minutes on a click,[11] with a standard deviation of 3.07 minutes.[11] In Figure 5, we display the distribution of search duration for clicked restaurants, showing a large variation in search duration, with many clicks lasting less than one minute and a large right tail. To provide external validation for this result, we use comScore to check the time spent on a similar website, and we find that click

Table 2. Restaurant Characteristics

	All		Clicked		Duration>median		Purchased	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
List page information								
Rating	2.71	0.32	2.72	0.31	2.74	0.29	2.78	0.25
Price	13.76	13.86	13.27	11.50	13.15	10.21	12.24	5.63
Promotion	0.20	0.40	0.24	0.43	0.27	0.45	0.30	0.46
Number of reviews	0.47	0.62	0.49	0.61	0.53	0.60	0.61	0.55
Position	5.59	3.03	5.10	3.04	5.15	3.07	4.98	3.08
Restaurant page information								
Average review length			0.37	0.18	0.38	0.19	0.41	0.19
Number of photos			85.01	100.37	94.23	101.37	104.18	97.69
Length of introduction			98.54	49.44	103.26	45.33	112.54	32.25
Observations	343,270		50,439		25,226		7,538	

Figure 5. Extent of Search on the Intensive Margin: Search Duration



Notes: This figure provides a histogram of duration (minutes) for observations with full duration information (no imputed values). The spike at the right tail is due to truncation and the collapse of duration longer than 10 minutes (the 90th percentile).

duration on Yelp is 3.55 minutes (January 2013), which is similar to duration in our data. Also, this finding is generally in line with estimates from the literature. More precisely, Fradkin (2017) reports that on Airbnb consumers spend 58 minutes before sending contact information to sellers and browse on average 31 listings, implying an average time spent on any listing of 1.87 minutes. In contrast, although consumers spend a relatively long time searching each restaurant, their search on the extensive margin (that is, the number of restaurants clicked) is small. More precisely, we find that 60% (71%) of sessions (queries) have only one click, with an average (median) click number by session of 2.83 (1). Correspondingly, at the query level, the average (median) click number is 1.44 (1). Thus, even when consumers search very few restaurants, they search each option intensively.

4.4.2. What Influences Search Duration? We showed that search duration is considerable. Next, we ask what influences the consumer's search duration decision, by considering two related questions. First, which restaurant and consumer characteristics affect search duration? To answer this question, in Table 2 in Online Appendix D, we regress search duration on restaurant characteristics displayed on the list and the restaurant pages, as well as on the consumer's prior experience with the website (measured by the number of days since website registration). Focusing on the list page information, we find that cheaper restaurants with a higher rating, that are promoted and that are displayed lower on the list page (higher position) lead to a higher search duration. Also, the more information is displayed on the restaurant page, for example, in terms of a larger number of photos, longer description of the restaurant or longer reviews, the more time consumers spend reading about the restaurant. In terms of consumer characteristics, we find that less experienced consumers spend a longer time searching.

Second, we investigate the relation between search duration and search order. To this end, we restrict our attention to sessions (or queries) with at least three clicks, and compute the average click duration for the first, last, and middle clicks. Figure 1 in Online Appendix D shows our results. We find that consumers spend more time on the first and last clicked restaurant in a session (or query) than on middle clicks.[13]

4.4.3. Relation between Search Duration and Purchases. Finally, we consider the relation between search duration and the probability of purchasing the searched restaurant. A t-test reveals that clicked restaurants that were purchased have a higher search duration (1.52 minutes difference, $t = -40.31$) than those that were not purchased. To further decompose this effect, we condition on clicks, and model the purchase decision in a session as being influenced by duration, restaurant, and consumer characteristics. We include an outside option in the model, meant to represent the option of not purchasing, which has an expected utility normalized to zero.[14] We report our results in Table 3 in Online Appendix D. We find that duration is correlated to purchases, even after accounting for restaurant and consumer characteristics.

In sum, in this section, we have shown that (a) consumers spend a considerable amount of time searching, even when they search few products; (b) search duration increases with consumer inexperience and the amount of information displayed on the restaurant pages; and (c) search duration is higher for purchased restaurants. Based on these results we build our empirical model, which we describe in the next section.

5. Estimation and Identification

5.1. Empirical Model

In Section 3, we developed a sequential search model that accounts not only for the consumer's decision of which products to search and whether to purchase but also for her search duration decision. We now consider an empirical application of this model that uses the data introduced in the previous section. To this end, we show how to adjust the model to the empirical setting considered and describe the estimation procedure we use to recover consumer preference, search costs and prior beliefs parameters.

The empirical context of our paper is consumer search for restaurant information on an Asian review website.

After visiting the homepage of the website, a consumer $i \in \{1,\ldots,N\}$ types in a query and observes a list of restaurants, with an individual restaurant on this list denoted by $j \in \{1,\ldots,J\}$. On the list page, the consumer observes some information about each restaurant, but can search by navigating to the restaurant page to obtain additional information about it. Each time period $t = 1,\ldots,T$, the consumer decides whether to continue searching, in which case she chooses a restaurant to search (including a previously searched option) or whether to stop, in which case she decides which restaurant to purchase, if any. Deciding not to purchase is interpreted as choosing the outside option (denoted by $j = 0$).

The consumer's utility from purchasing restaurant j in period t is equal to

$$u_{ijt} = X_j^{\text{list}}\beta_i + \mu_{ijt} + \epsilon_{ij}. \tag{11}$$

We model a consumer's utility from purchasing restaurant j in period t as having three components. First, the consumer values the characteristics of each restaurant revealed on the list page before search. Some of this information is observable to researchers, X_j^{list}, while other information is hidden from the researcher and modeled as an idiosyncratic shock, $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$. We assume consumers observe this information without paying a search cost, consistent with prior literature (Kim et al. 2010, 2017; Chen and Yao 2016; De los Santos and Koulayev 2017). In addition to these pieces of information, by searching j, the consumer obtains additional information from the restaurant page. The longer she spends searching j, the more information she obtains. However, search does not reveal all uncertainty about j. Instead, μ_{ijt} represents the consumer's perceived match value at t with restaurant j. We normalize the expected utility of not purchasing, that is, choosing the outside option, to zero so that $u_{i0} = \epsilon_{i0}$.

Consumer learning is modeled as in Section 3. More precisely, the consumer is uncertain about her match value with a restaurant j, which we assume is drawn independently from $N(\mu_{ij}, \sigma_j^2)$, with unknown mean μ_{ij} and known variance σ_j^2. To resolve this uncertainty, the consumer spends time searching restaurants. To model search duration, we will interpret time spent searching an option as searching the same option multiple times (e.g., spending five minutes on a restaurant will be equivalent to searching it five times). The consumer begins her search with a prior belief about the match value, summarized by $N(\mu_{ij0}, \sigma_j^2/n_{ij0})$. Without data on consumer prior uncertainty at the product level, we need to assume $\mu_{ij0} = \mu_{i0}$ and $n_{ij0} = n_{i0}$, for all j. However, we do observe the level of experience of the consumer with the website, measured by the number of days since the consumer registered on the website, so we can use it to capture the degree of heterogeneity in the consumers' prior uncertainty. Because n_{ij0} gives the number of samples assumed by the prior belief distribution, it is positive, so we model it using an exponential function. Thus, in estimation, we use $n_{i0} = exp(m_{i0} + E_i\delta_i)$, where m_{i0} is the consumer-specific mean prior uncertainty, and E_i denotes the level of experience of the consumer.

By searching j in period t, the consumer observes a signal of the restaurant's match value, given by $s_{ijt} \sim N(\mu_{ij}, \sigma_j^2)$. We model signals as a function of restaurant page information, as follows:

$$\mu_{ij} = \mu_i + X_j^{\text{rest}}\alpha_i. \tag{12}$$

Using Bayes' rule, the consumer updates her belief about a restaurant's match value given this additional information. More precisely, searching j at t implies a posterior belief $N(\mu_{ijt+1}, \sigma_j^2/n_{ijt+1})$, with $\mu_{ijt+1} = \frac{n_{ijt}\mu_{ijt}+s_{ijt}}{n_{ijt+1}}$ and $n_{ijt+1} = n_{ijt} + 1$, while for $k \neq j$, $\mu_{ikt+1} = \mu_{ikt}$ and $n_{ikt+1} = n_{ikt}$, that is, options that are not searched are not updated. The posterior mean is what affects the consumer's purchase decision. Note that even though prior uncertainty is not product specific, through search n_{ijt} will vary by products.

To obtain restaurant page information, the consumer pays a cost of c_{ij} per search. To ensure that search costs are positive, we model c_{ij} as an exponential function,

$$c_{ij} = exp(k_i + P_j\gamma_i), \tag{13}$$

where k_i is the consumer-specific mean search costs, and P_j denotes factors that affect the consumer's search cost for j (e.g., the restaurant's position) (Ursu 2018).

The empirical model differs in two respects from the one presented in Section 3. First, motivated by the empirical application, consumers have access to list page information before search. This information is available without paying a search cost and influences the consumer's utility. Thus, consumers search to obtain information on μ_{ijt}, but are certain about the list page information observed. Second, restaurant page information influences the signals that the consumer observes through search. This assumption is motivated by our results in Table 2 in Online Appendix D showing that search duration is affected by the information revealed on the restaurant page. In our model, restaurants with more favorable restaurant page information imply more favorable signals, making the consumer more likely to search those longer.

5.2. Likelihood Function

To estimate the model, we use the optimal search rules in Section 3.2 to construct the likelihood of consumer search, search duration, and purchase decisions. The optimal search rules translate into the following restrictions on the parameters of interest. Suppose the consumer searched an option in each of the $t \le T_i$ periods, with period T_i denoting the final period in which consumer i searches. Then, in period $T_i + 1$ we observe the consumer making a purchase or choosing the outside option of not purchasing. In this case, the stopping rule imposes two types of restrictions on parameters. First, in all periods $t \le T_i$ when the consumer i searched a restaurant, for the searched option $j \in \{1, \dots, J\}$ it must be that

$$M_{ijt}(c_{ij}, \sigma_j, n_{ijt}) - \Delta_{ijt} > 0, \tag{14}$$

where $\Delta_{ijt} = |u_{ijt} - \max_{k \neq j} u_{ikt}|$ for $k \in (0, 1, \dots, J)$.

Second, in period $T_i + 1$ when the consumer does not search, it must be that

$$M_{ijT_i+1}(c_{ij}, \sigma_j, n_{ijT_i+1}) - \Delta_{ijT_i+1} < 0, \quad \forall j \in \{1, \dots, J\}. \tag{15}$$

The selection rule requires that, if the consumer searched $j \in \{1, \dots, J\}$ at $t \le T_i$, then

$$\frac{M_{ijt}(c_{ij}, \sigma_j, n_{ijt}) - \Delta_{ijt}}{c_{ij}^{1/3}\sigma_j^{2/3}} > \max_{k \neq j} \frac{M_{ikt}(c_{ik}, \sigma_k, n_{ikt}) - \Delta_{ikt}}{c_{ik}^{1/3}\sigma_k^{2/3}}, \quad \forall k \in \{1, \dots, J\}. \tag{16}$$

Finally, consistent with the choice rule, if the consumer chooses j (including the outside option) after terminating search, it must provide her with the largest posterior expected utility among her options. Formally,

$$u_{ijT_i+1} \ge \max_{k \neq j} u_{ikT_i+1}, \quad \forall j, k \in \{0, 1, \dots, J\}. \tag{17}$$

If consumers search sequentially, they make search, search duration and purchase decisions jointly. Thus, the probability of observing a certain outcome in the data in period t for consumer i is characterized by the joint probability of the stopping, selection and choice rules holding in that period, as given by

$$L_{it} = \Pr(\text{Stopping rule}_{it}, \text{Selection rule}_{it}, \text{Choice rule}_{it}). \tag{18}$$

Because consumers make these three decisions jointly, the likelihood function does not have a closed form solution. As a result, we use a simulated maximum likelihood (SMLE) approach to estimate the parameters of the model. In choosing the simulation method, we follow McFadden (1989), Honka (2014), Honka and Chintagunta (2017), and Ursu (2018) and use the logit-smoothed AR simulator.

Simulation using the logit-smoothed AR simulator involves the following steps:

1. For each consumer, determine the last period of search T_i.
2. Make $d = \{1, \dots, D\}$ draws of ϵ_{ij} for each consumer-product combination.
3. For each ϵ_{ij} draw, make $f = \{1, \dots, F\}$ draws of s_{ijt}.
4. Compute search costs c_{ij}, use draws in steps 2 and 3 and Bayesian updating formulas in Equation (5) to form u_{ijt}, M_{ijt}, and Δ_{ijt}.
5. Use the stopping, selection and choice rules to construct the following expressions:
   (a) $\nu_{it}^1 = M_{ijt} - \Delta_{ijt}$ for the searched option $j \in \{1, \dots, J\}$ and $t \le T_i$.
   (b) $\nu_{iT+1}^2 = \Delta_{ijT_i+1} - M_{ijT_i+1}, \quad \forall j \in \{1, \dots, J\}$.
   (c) $\nu_{it}^3 = \frac{M_{ijt} - \Delta_{ijt}}{c_{ij}^{1/3}\sigma_j^{2/3}} - \max_{k \neq j} \frac{M_{ikt} - \Delta_{ikt}}{c_{ik}^{1/3}\sigma_k^{2/3}}$ for the searched option $j \in \{1, \dots, J\}$, any other option $k \in \{1, \dots, J\}$, and $t \le T_i$.
   (d) $\nu_{iT+1}^4 = u_{ijT_i+1} - \max_{k \neq j} u_{ikT_i+1}, \quad \forall j, k \in \{0, 1, \dots, J\}$.
6. Compute expression

$$R_i = exp\left(-\lambda_2 \nu_{iT_i+1}^2\right) + exp\left(-\lambda_4 \nu_{iT_i+1}^4\right) + \sum_{t=1}^{T_i} \left[exp\left(-\lambda_1 \nu_{it}^1\right) + exp\left(-\lambda_3 \nu_{it}^3\right)\right], \tag{19}$$

where $(\lambda_1, \dots, \lambda_4) > 0$ are scaling parameters.

7. Obtain $R = \sum_i R_i$ by summing over consumers and compute S

$$S = \frac{1}{1 + R}. \tag{20}$$

8. The average of S over the D and F draws of the error terms gives the simulated likelihood function.

Unlike previous work using the logit-smoothed AR simulator that uses a single scaling parameter for all search rules (McFadden 1989, Honka 2014, Honka and Chintagunta 2017, Ursu 2018), we use four different values corresponding to consumers' four decisions rules (in steps 5a–5d). Compared with using a single parameter for all rules, our choice allows us to better recover the parameters of the model, by assigning more weight in the likelihood function to the choice rule and the stopping rules. Online Appendix B describes in more detail how we determine the values of these scaling parameters.

We capture consumer heterogeneity in the model using a latent class approach. To construct the likelihood function in the case of one consumer segment, we consider consumer choices at the query level. The set of options that is available for search is the set of restaurants displayed in the query. To construct the likelihood function in the case of more than one consumer segment, we assume that all queries that correspond to a certain session belong to the same segment. Thus, we need to compute the likelihood function across all queries in a session, conditional on belonging to a segment, and take the weighted sum of the conditional likelihoods (with the segment sizes serving as weights).

5.3. Identification

In this section, we describe how the parameters of our model are identified. We start with a description of our argument, and then proceed with the formal identification strategy.

We seek to identify three types of parameters: preference, search costs, and prior beliefs parameters (which form the basis of the learning process). Our identification argument reflects the fact that we combine a model of consumer sequential search with a Bayesian learning model. Thus, an intuitive way to see how the model is identified is to first think how the parameters of a sequential search model are identified in the absence of search duration data, and then to ask how data on search duration helps identify additional parameters. To be more precise, without search duration data, observing which products are searched, in what order, and whether consumers purchase, identifies preference and search costs parameters as is standard in the literature (Chen and Yao 2016, Honka and Chintagunta 2017, Ursu 2018). For instance, preference parameters are identified from the correlation in product characteristics and the frequency with which products are searched and purchased in the data. Search costs do not affect purchase decisions, and are identified by observing the consumer's consideration set, that is from the stopping rule, imposing an upper and a lower bound on the mean search cost that must have made if optimal for the consumer to perform a certain number of searches. By observing search duration (and revisit) data and treating each unit of time as a signal, we can additionally identify the prior beliefs parameters from the purchase probability of consumers with different information accumulated through search (similar to Erdem and Keane 1996, Narayanan et al. 2005, Ma 2016).

More formally, the set of parameters to estimate is composed of the following: list and restaurant page preference parameters (β_i, α_i), learning parameters $(\mu_{i0}, m_{i0}, \delta_i, \mu_i, \sigma_j^2)$, search costs parameterized by (k_i, γ_i), and the variance of the unobserved idiosyncratic shock (σ_ϵ^2). In the specific empirical setting in which we estimate our model, certain normalizations are needed for identification. First, as is typical in Bayesian learning models, we can only recover the ratio of the prior and the signal variance, which implies that we will not be able to estimate σ_j^2, but can estimate the parameters in n_{i0}. For this reason, we fix $\sigma_j^2 = 1$, for all restaurants. Second, we fix $\sigma_\epsilon^2 = 1$, as is common in the literature (see, e.g., Kim et al. 2010, 2017; Chen and Yao 2016; Honka and Chintagunta 2017). The variance of the unobserved idiosyncratic shock affects the benefits from search, but unfortunately our data do not allow us to separately identify it from search costs except through functional form (see Dong et al. 2018 for a more detailed description of this issue). Given these considerations, the set of parameters we seek to identify becomes $(\mu_{i0}, \mu_i, \beta_i, \alpha_i, m_{i0}, \delta_i, k_i, \gamma_i)$.

The data provide information on three types of choices that consumers make. First, conditional on a query, we observe consumers' consideration sets: which restaurants consumers searched and which ones they ignored. Second, we observe search duration, that is the number of minutes a consumer spent on each searched restaurant page, and whether the restaurant was revisited. Finally, we observe whether the consumer chooses to purchase one of the searched restaurants or whether she chooses the outside option of not purchasing. These choices together with the optimal search rules we presented in Section 3.2 constitute the necessary components of our identification argument.

Preference parameters for characteristics that vary by restaurant (β_i, α_i) are identified from the correlation in restaurant characteristics displayed on the list and the restaurant pages and the frequency with which restaurants are searched and purchased. For example, the odds of a consumer purchasing a restaurant with a higher rating or with more favorable restaurant page information reveals consumers' weights for these restaurant characteristics.

Learning parameters are identified from the purchase probability of consumers with different information accumulated through search (similar to Erdem and Keane 1996, Narayanan et al. 2005, Ma 2016). More precisely, as consumers gather more information by searching, prior uncertainty reduces to zero, mean beliefs converge to the true match value, and purchase decisions (the choice rule), as in standard choice models, allow us to identify the mean match value (μ_i), in addition to the preference parameters (β_i, α_i). In contrast, consumers who have searched less, base their purchase decisions more on priors, helping identify prior mean beliefs (μ_{i0}, m_{i0}) from the mean and the variance of purchase probabilities of such consumers in the data. Variation across consumers in their prior experience and their search and purchase prevalence identifies δ_i.

The identification of prior uncertainty and search costs in our model relies on functional form. More precisely, the specific form of the selection rule provides parametric identification for these two consumer primitives. The selection rule dictates when the consumer should continue searching the same option or when she should switch, conditional on search not ceasing. Regardless of the number of times the consumer searches an option, search costs per option per minute remain unchanged. However, the more the consumer searches an option, the lower her uncertainty becomes. Thus, observing when a consumer decides to switch to searching another option reveals her prior uncertainty level (e.g., switching after having searched for a long time rather than immediately suggests a relatively higher prior uncertainty). In Online Appendix E, we describe a simplified version of the model that further details this argument. In addition, in the same appendix, we show that changing prior uncertainty and search costs leads to different shapes in the number of searches and the duration of search per product, further aiding our identification argument.

As is typical in consumer search models, search costs are identified, because they do not affect purchase decisions and thus do not enter the choice rule. The stopping rule imposes upper and lower bounds on the mean search costs (k_i) that must have made it optimal for the consumer to search a certain number of restaurants and for a certain number of minutes. For example, continuing to search when the benefit is low implies low search costs, ceteris paribus. The level of search costs is pinned down by the functional form of the boundary of search and the distribution of the utility function error terms. The product-specific search cost (γ_i) is identified from both the stopping and the selection rules, more precisely from differences in search odds of restaurants with different characteristics. For example, restaurants ranked at the top of the list page may be searched more frequently, implying lower search costs than those ranked closer to the bottom (higher position).

An additional obstacle to identifying model parameters is that the price of a restaurant in our data may be endogenous. For example, unobserved quality shocks may affect both consumer choices and restaurant prices, or consumer-specific choice probabilities may affect restaurants' pricing decisions. However, concerns about endogeneity should be minimized in our setting for two reasons: first, restaurant prices are based on a menu that does not change in response to individual consumer queries or frequently over time (our observation period is three months); second, we observe and control in the model for any promotions that restaurants run. For these reasons, we choose to only include the observed price in our model.

5.4. Monte Carlo Simulation

In what follows, we show that Simulated Maximum Likelihood using the logit-smoothed AR simulator can recover the parameters of this model. We do so with Monte Carlo simulation. More precisely, we generate a data set of 2,000 consumers making choices among five options (one outside option and the rest restaurants). Restaurants have both list and restaurant page characteristics, which we assume are drawn from a normal distribution with mean and standard deviation equal to those found in the data. After search ceases, the consumer chooses whether to purchase from a restaurant on the list (with varying search duration) or whether to choose the outside option, which has expected utility normalized to zero. For estimation, we follow the steps described in Section 5 and use 100 draws from the distribution of the utility error terms and 30 draws from the signals distribution for each consumer-restaurant-time period combination. We simulate 50 different data sets using the same true parameters, but different seeds for the utility error terms, and repeat the estimation for each data set. Our Monte Carlo simulation results can be found in Table 3.[15] The first column shows the true parameters; the second column shows the mean of the estimated parameters across the 50 simulations; and the last column gives the standard deviation of the mean across these simulations. We find that our method recovers the parameters of the model well.

5.5. Estimation Sample

Before discussing our results, we clarify a few data choices we make to help with the interpretation and estimation of the model. First, restaurant characteristics vary in their scale, so we choose to demean the following restaurant characteristics to make them comparable: rating, price, number of reviews, number of photos, average review length, and the length of the introduction. Second, we create an outside option, with an expected utility normalized to zero, to represent the choice of not purchasing. Note that although the model allows for the possibility of consumers choosing an option they did not search, we do not observe such behavior in the data. Third, we discretize search duration and round it up to one-minute increments. This assumption will only affect the units in which we express the mean search cost estimate. Finally, to make the estimation feasible, we restrict the data sample as follows. We only consider queries for which we observe search duration

Table 3. Monte Carlo Simulation Results

	True values	Estimates	SD
List page information (β)			
Rating	1	0.9344	(0.0280)
Price	–2	–1.8708	(0.0410)
Restaurant page information (α)			
Average review length	1	1.0130	(0.0690)
Learning			
Prior mean μ_0	2	2.0844	(0.1039)
Prior uncertainty $1/n_0$ (exp)	–1	–0.8048	(0.0313)
Signal mean μ	1	1.1021	(0.1147)
Search cost c (exp)			
Constant	–3	–3.3395	(0.0552)
Log-likelihood		–8,196	
Observations		10,000	

information for all searches made. We estimate the model at the session level, where each session can have one or more queries. We restrict our attention to sessions with at most four queries, which represent 91% of sessions in the data. Finally, we randomly select a subsample of 1,000 sessions for estimation. This leads to a data set with 14,779 observations and 1,367 queries, of which 26% lead to a transaction (similar in magnitude to the conversion rate in the full data set).

In sum, in this section, we outlined the estimation and identification strategy of our model. Next, we present results of our estimation.

6. Results

In this section, we present estimation results using the sequential search model and the estimation procedure presented in previous sections. We account for consumer heterogeneity in estimation by using a latent class approach to estimate the parameters of the model across segments. The model is estimated using simulated maximum likelihood with the logit-smoothed AR simulator. For the estimation, we use 25 draws from the distribution of the utility error terms and 15 draws from the distribution of signals for each consumer-restaurant-time period combination.[16] We repeat the estimation 50 times and present mean results across these 50 separate estimations.

Table 4 presents our estimation results.[17] Column 1 presents results from the case where consumers are homogenous, and columns 2 and 3 show our results with heterogeneity. In column 1, we generally find utility and search cost estimates that are economically meaningful and significant. In particular, in terms of characteristics observed on the list page, we find that higher ratings, more promotions and more reviews, increase utility, while higher prices decrease utility. A distinguishing feature of our model is that it allows us to estimate not only consumer preferences for characteristics observed before search (list page information) but also their preferences for information observed after search (restaurant page information). We find that a longer introduction and longer reviews may increase consumer utility. However, these effects are not significant, possibly suggesting that the mean signal effect captures most of the variation in choices conditional on observing restaurant

Table 4. Estimation Results

	One segment		Two segments			
			Segment 1		Segment 2	
	(1)		(2)		(3)	
	Estimates	SE	Estimates	SE	Estimates	SE
List page information β_i						
Rating	0.0823***	(0.0129)	0.0884***	(0.0129)		
Price	−0.0526***	(0.0162)	−0.0355*	(0.0183)	−0.0940***	(0.0221)
Promotion	0.2344***	(0.0263)	0.2357***	(0.0209)		
Number of reviews	0.0487***	(0.0119)	0.0491***	(0.0130)		
Restaurant page information α						
Average review length	0.0120	(0.0330)	0.0109	(0.0337)		
Number of photos	−0.0295	(0.0395)	−0.0346	(0.0323)		
Length of the introduction	0.0318	(0.0412)	0.0414	(0.0343)		
Learning						
Prior mean μ_{i0}	−1.4766***	(0.0170)	−1.2115***	(0.0325)	−1.7449***	(0.0264)
Prior uncertainty $1/n_{i0}$ (exp)						
Constant m_{i0}	1.7823***	(0.0181)	1.6740***	(0.0208)	2.0573***	(0.0509)
Experience δ	0.0049	(0.0112)	0.0098	(0.0071)		
Signal mean μ_i	−0.0488	(0.0304)	0.3301***	(0.0476)	−0.5015***	(0.0553)
Search cost c_{ij} (exp)						
Constant k_i	−8.2166***	(0.0577)	−8.0698***	(0.0623)	−8.5963***	(0.1150)
Position γ	0.0604***	(0.0085)	0.0638***	(0.0054)		
Probability segment 1						
π			−0.0304	(0.3613)		
Log-likelihood	−8,575		−8,527			
AIC	17,177		17,092			
BIC	17,276		17,237			
Observations	14,779		14,779			

Notes. Standard errors are in parentheses. Parameters not reported under segment 2 are the same as those for segment 1.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

page information. We find mixed evidence for the effect of photos, suggesting that more photos may decrease utility (insignificant, possibly negative due to nonlinearity).

In terms of search costs, we find that they are higher for restaurants displayed lower on the ranked list page and that mean search costs are relatively low. More precisely, we find mean search costs of approximately \$0.07 per minute spent searching.[18] To the best of our knowledge, ours is the first paper to quantify consumer search costs per minute from a structural model of consumer search.[19] Most other papers in the literature focus on quantifying search costs per product (Hong and Shum 2006, De los Santos et al. 2012, Honka 2014, Koulayev 2014, Chen and Yao 2016, De los Santos and Koulayev 2017, Honka and Chintagunta 2017, Ghose et al. 2019). Given an average search duration of 3.47 minutes in our data, we can also approximate search costs per restaurant to equal \$0.25.

Our mean search cost estimate is lower than most prior estimates found in the literature. The fact that we account for search duration, not only search and purchase decisions, can provide one explanation for this difference. For example, prior work finds search costs ranging from \$1.35 to \$29.40 for an additional book searched when the average number of searches is less than 3 (Hong and Shum 2006, De los Santos et al. 2012); \$3.43 to \$55.23 for another hotel searched when the number of searches ranges from 0.33 to 2.3 (Koulayev 2014, Chen and Yao 2016, De los Santos and Koulayev 2017, Ghose et al. 2019); \$41.81 to \$42.09 for an auto insurance quote when consumers obtain on average 2.96 quotes (Honka 2014, Honka and Chintagunta 2017); and \$0.25 for another search on eBay across various categories (Blake et al. 2016). In our data, 60% of sessions contain only one restaurant searched, with an average of 2.83 restaurants searched across sessions. Despite the low number of searches, the average search duration is 3.47 minutes per restaurant. In the absence of information on search duration, the fact that consumers search few options would suggest that their search costs are high, ceteris paribus. However, as our search cost estimate demonstrates, the fact that consumers search few options does not necessarily suggest large search cost, if they spend a long time searching.

Most sessions do not lead to a transaction regardless of the time spent searching, so we find that mean prior beliefs (μ_{i0}) and the signal mean (μ_i) are negative. However, the difference between these two parameters shows that consumers start their search with relatively poor expectations about product matches, but these improve through search. Consistent with our previous results in Section 4.4, this shows that consumers are more likely to purchase a restaurant they spend more time searching.

Another advantage of our proposed model is that it allows us to quantify the extent to which consumer prior uncertainty influences the search process. In our data, the prior uncertainty parameter is estimated to be significant, and is relatively high, rationalizing consumers' choice to spend a considerable amount of time searching each restaurant. In addition, this effect varies across consumers. More precisely, those consumers who begin their search having more experience on the website, exhibit lower prior uncertainty, thus having to search less.

To account for consumer heterogeneity, we estimate the model using a latent class approach with one, two, and three consumer segments. We find that the data favor the model with two segments of consumers, and present those results in columns 2 and 3.[20] The two segments are approximately equal in size ($1/(1+exp(\pi)) = 0.5076$), but differ in their preferences, search costs, and prior beliefs parameters. More precisely, the first segment is relatively less price sensitive, begins search with more favorable prior expectations (higher prior mean μ_{i0}), and is more likely to buy after searching (positive signal mean, μ_i). In addition, the first segment begins search with higher uncertainty and has higher search costs than the second segment. This suggests that the first segment of consumers searches few options but for a long time, while the second segment searches many options but spends a relatively shorter amount of time searching. Without information on search duration, such differences in behavior would be attributed only to differences in preferences and search costs, likely biasing these estimates.

7. Counterfactual Analysis

In this section, we analyze through counterfactuals whether changing the amount of product information provided to consumers upon search benefits sellers, platforms or consumers. Determining how much information to provide consumers is of managerial relevance to many companies, such as search intermediaries or online platforms. Such companies face a trade-off: providing too much information may prevent consumers from searching enough products, while providing too little information may prevent them from acquiring the necessary information to make a purchase decision. Our model of sequential search, which endogenizes the intensive and the extensive margins of search, is well suited to help companies resolve this a trade-off. To illustrate, we perform two counterfactuals related to the amount of information to reveal to consumers. First, we ask whether the review website in our data application would benefit from increasing the amount of information it is providing to consumers, or whether it is already providing too much information. Second, we ask whether the amount of information displayed to consumers upon search should be taken into account when the company ranks/orders products.

To perform these counterfactuals, we use the parameter estimates from the previous section (column 1 of Table 4) and simulate consumer choices using the model presented in Section 3. To integrate over the distribution of unobserved components in the model (the unobserved utility and the signal shock), we repeat the simulation 25 times (fives times for each unobserved shock) and report the mean of the results we obtain. Consumers' simulated choices in two scenarios, where we change the product information provided to them, are compared with the current setting where no such change occurs. In these simulations, the available set of products to search remains the same (the same restaurants displayed on the list page in a query), but we change certain aspects of the information the consumer observes about these restaurants. Because our data contains restaurant page information only if the consumer searched, but list page information for all observations, we impute missing information using the coefficients obtained from a regression run on the nonmissing observations of list page on restaurant page characteristics.

The results from our counterfactuals can be found in Table 5.[21] These results represent short run effects of changing the restaurant page information. The table provides results on the following outcomes: the percentage change in (1) the number of restaurants searched in the query; (2) the search duration; and (3) the number of transactions. Also, for consumers who made a purchase, we report the percentage change in the price paid and in consumer welfare (defined here as the difference in consumers' utility of the purchases made net of their total search costs). Generally, the effects we find are modest, but as we show, accord with our intuition in terms of directionality.

In columns 1 and 2 of Table 5, we seek to answer the first question, of whether sellers should increase the amount of information provided to consumers. In the first column, we find that if sellers increase the length of their descriptive introduction on the restaurant page, the consumer's utility from searching a given option increases, leading to higher transactions. In addition, we find that this change leads to fewer searched options and to a shorter search duration. Recall that our model predicts that both options with very large and those with very small utility might not be searched by the consumer. Thus, our result suggests that the increase in utility is sufficient for the consumer to want to stop searching. Also, we show that the consumer is willing to pay a higher price for purchasing a restaurant, because she is compensated by higher utility and lower search costs. Such a change would benefit not only consumers but also the platform, through more transactions, higher revenue, and more expensive restaurants. In that sense, a longer description, providing more relevant information to consumers, is overall beneficial. In column 2, we find similar but larger effects when sellers increase the amount of desirable information revealed upon search (given our results in Table 4, this corresponds to increasing the introduction and the review length but decreasing the number of photos). The change in transactions obtained in column 2 is equivalent to approximately a 20% reduction in prices in the absence of a change in information, demonstrating the importance of increasing information desirability.

Column 4 in Table 5, provides our answers to the second question, of whether the company should take into account the amount of information displayed to consumers upon search when ranking restaurants. To perform this counterfactual, we reorder the restaurants displayed in a consumer's query by their total utility, computed using restaurant characteristics displayed on the list page, the amount of information revealed upon search on the restaurant page, and the coefficients estimated in column 1 of Table 4. We then simulate consumer choices under the new ranking. We contrast this result with that in the literature (shown in column 3), focusing on ranking options by their utility given only list page characteristics (Ghose et al. 2012, 2014; Chen and Yao 2016; Ursu 2018),

Table 5. Counterfactual Results

	Amount of information		Ranking	
Percentage change	Longer introduction (1)	Longer introduction and reviews; fewer photos (2)	Order by list page utility (3)	Order by total utility (4)
Restaurants searched	−0.50	−1.11	0.01	0.10
Average search duration	−0.85	−2.00	1.26	1.61
Total transactions	0.08	0.21	0.22	0.20
Price of purchased restaurant	0.12	0.17	−0.39	−0.18
Consumer welfare	1.31	2.78	0.32	0.31

Note. Variables in columns 1 and 2 are changed by one standard deviation.

ignoring in the ranking the amount of information revealed through search. Reordering hotels, either using only the list page information, or both list and restaurant page information, increases the number of restaurants searched, the search duration and transactions, benefiting consumers. However, effects on short term revenues differ between the two rankings. When ordering by list page information, consumers buy significantly cheaper options (price appears on the list page), lowering revenues for sellers and the platform, although transactions increase. This effect is reversed when taking restaurant page information into account in the ranking, leading to a much lower decrease in prices paid, and an increase in revenues. Thus, our results suggest that a ranking accounting for the amount of information displayed to consumers would benefit both the company and the consumer, further highlighting the importance of modeling search duration.

In sum, a model that accounts for the intensive margin of search provides new and valuable insights to managers that would not be possible otherwise. More precisely, we find that understanding what drives search duration can help managers decide how much information to provide to consumers upon search.

8. Conclusion

In this article, we study consumers' decision to spend time searching, in addition to the decision of which products to search and whether to purchase. To this end, we develop a sequential search model in which consumers are uncertain about their match value for a product and search to reveal (noisy) signals about it. Consumers then use these signals to update their beliefs about products searched in a Bayesian fashion. We model search duration as the consumer's decision to search the same product multiple times. We build on the framework by Chick and Frazier (2012) to describe the optimal search rules for the consumer and develop the model's empirical counterpart, which we then estimate using data on consumers searching for restaurants on an Asian review website. We document that search duration is considerable, that consumers search few options, and that restaurants that are searched longer are more likely to be purchased. Estimating our model on these data allows us to quantify consumer preference, search cost, and prior beliefs parameters. Finally, we develop managerial implications related to the amount of information companies should provide to consumers, given that this will affect search duration and thus search and purchase decisions. Our approach provides a general framework to study consumer engagement with a product through search and also can be used to capture a consumer's decision to revisit a previously searched product to resolve further uncertainty.

While our approach provides one way in which the duration of search can be endogenized, there could be other approaches that need to be explored given the empirical importance of the duration decision. Four other potentially useful extensions of our study are the following. First, looking at search within and across sessions would result in a more complete picture of the search process for a product or service. Second, a validation of our counterfactual predictions in the context of a field study would enhance our understanding of the benefits of considering duration data when analyzing search behavior. Third, our approach allows researchers to also model revisits. However, we do not observe what information consumers check when they search or revisit. With such data, a managerially relevant question to ask is whether consumers revisit products for the same or for new information and how this relates to their final purchase decisions. Finally, analyzing additional managerial implications of our results beyond our counterfactuals, for example, ones related to targeting consumers based on their estimated prior awareness, would be valuable. We leave these and other related topics to future research.

Acknowledgments

The authors are thankful for comments from Jason Abaluck, Paulo Albuquerque, Simon Anderson, Ron Berman, Eric Bradlow, Bart Bronnenberg, Stephen Chick, Babur De los Santos, J.P. Dube, Daria Dzyabura, Tulin Erdem, Pedro Gardete, Wesley Hartmann, Elisabeth Honka, Ali Hortacsu, Xiao Liu, Xueming Luo, Carl Mela, Eitan Muller, Harikesh Nair, Sridhar Narayanan, Thomas Otter, Navdeep Sahni, Stephan Seiler, Andrey Simonov, Miguel Villas-Boas, Russell Winer, and Pinar Yildirim; seminar participants at Stanford University, Wharton Marketing Camp, Virginia University, and Temple University; and attendees of the 2017 Marketing Science/INFORMS, 2017 QME, 2018 SICS, 2019 Choice Symposium, and 2019 Workshop on Consumer Search and Switching Costs conferences for their thoughtful comments. The feedback from two reviewers, an associate editor, and the senior editor is also gratefully acknowledged. The usual disclaimer applies.

Endnotes

[1] Branco et al. (2016) study this problem theoretically. We contribute by estimating a model of search duration and using a counterfactual to empirically determine an answer.

[2] Consumers search to learn about μ_{ijt} and know ϵ_{ij} before search. Thus, the search rules derived by Chick and Frazier (2012) that we present below (Section 3.2) apply to our case.

[3] This is the approach recommended by Chick and Frazier (2012), because of its ease of implementation.

[4] Note that the expression for $\hat{b}(h)$ when $h > 40$ has been updated relative to Chick and Frazier (2012) using results in Chernoff (1965). This update has been mentioned in Chick et al. (2018) and the code is available at https://github.com/sechick/pdestop.

[5] To ensure the anonymity of our data provider, Figure 4 provides screenshots from a different review website. The two review websites have a very similar structure.

[6] Restaurants are ordered by default according to the proprietary ranking algorithm used by the website. However, consumers can further sort or filter search results. Modeling such decisions is beyond the scope of this paper. The interested reader should refer to Chen and Yao (2016).

[7] The Wayback Machine website can be found at https://archive.org/web/.

[8] For our analysis in this section, we collapse revisits into the first click and sum the total duration. In estimation (Section 6), we use the raw data in order to capture revisits.

[9] We follow the policy of the website and weight taste by 0.6, ambience by 0.25, and service by 0.15 to construct the rating of a restaurant.

[10] We transform prices in dollars from RMD by multiplying by the exchange rate 0.1507 as of July 10, 2018.

[11] Considering only the observations for which we have full duration information (79% of clicks), the average (median) consumer spends 2.88 (1.45) minutes on a click, with a standard deviation of 3.21 minutes.

[12] We express duration here as follows: 1.50 minutes means 1 minute and 30 seconds.

[13] The same analysis by total click number shows a similar pattern and is available upon request.

[14] Including an outside option in the model increases the number of observations by the number of sessions.

[15] Additional results can be found in Table 6 in Online Appendix G.

[16] We also estimated the model with one segment of consumers with 50 draws from the distribution of the utility error terms and 30 draws from the distribution of signals. The results are very similar, so we opted for fewer simulations to save on computational time. Our results are available upon request.

[17] Online Appendix F shows that our results are robust to different starting values for our estimation.

[18] To compute mean search costs in dollars, we divide the search cost estimate by the unstandardized price coefficient (price coefficient estimated divide by its standard deviation in dollars, approximately $13)

[19] Seiler and Pinna (2017) measure the benefit of searching an additional minute to equal $2.10 by regressing price paid on search duration. In contrast, taking into account not only the price of the product but also the difference in restaurant characteristics searched versus not searched and in search duration, our structural model estimates lower search costs.

[20] Our results from the model with three segments can be found in Table 1 in Online Appendix C. The BIC increases to 17,287 and AIC increases to 17,097.

[21] The results of our counterfactuals should be interpreted with caution, because our analysis is based on simulating consumer choices using restaurant page parameters that are not significant in our main estimation.

References

Ackerberg D (2003) Advertising, learning and consumer choice in experience good markets: A structural empirical examination. *Internat. Econom. Rev.* 44(3):1007–1040.

Blake T, Nosko C, Tadelis S (2016) Return to consumer search: Evidence from eBay. Working paper, eBay Research Labs, San Jose, CA.

Branco F, Sun M, Villas-Boas JM (2012) Optimal search for product information. *Management Sci.* 58(11):2037–2056.

Branco F, Sun M, Villas-Boas JM (2016) Too much information? Information provision and search costs. *Marketing Sci.* 35(4):605–618.

Brezzi M, Lai T (2002) Optimal learning and experimentation in bandit problems. *J. Econom. Dynam. Control* 27(1):87–108.

Chen Y, Yao S (2016) Sequential search with refinement: Model and application with click-stream data. *Management Sci.* 34(4):606–623.

Chernoff H (1965) Sequential test for the mean of a normal distribution III (small t). *Ann. Math. Stat.* 36(1):28–54.

Chernoff H, Ray SN (1965) A Bayes sequential sampling inspection plan. *Ann. Math. Statist.* 36(5):1387–1407.

Chick SE, Gans N (2009) An economic analysis of simulation selection problems. *Management Sci.* 55(3):421–437.

Chick SE, Gans N, Yapar O (2018) Bayesian sequential learning for clinical trials of multiple correlated medical interventions. Working paper, INSEAD, Paris.

Chick S, Frazier PI (2012) Sequential sampling with economics of selection procedures. *Management Sci.* 58(3):1–16.

De los Santos B (2017) Consumer search on the internet. Working paper, Clemson University, SC.

De los Santos B, Hortaçsu A, Wildenbeest MR (2012) Testing models of consumer search using data on web browsing and purchasing behavior. *Amer. Econom. Rev.* 102(6):2955–2980.

De los Santos B, Hortaçsu A, Wildenbeest MR (2017) Search with learning for differentiated products: Evidence from e-commerce. *J. Bus. Econom. Statist.* 35(4):626–641.

De los Santos B, Koulayev S (2017) Optimizing click-through in online rankings for partially anonymous consumers. *Marketing Sci.* 36(4):542–564.

Dong X, Morozov I, Seiler S, Hou L (2018) Estimation of preference heterogeneity in markets with costly search. Working paper, Santa Clara University, Santa Clara, CA.

Dukes A, Liu L (2015) Online shopping intermediaries: the strategic design of search environments. *Management Sci.* 62(4):1064–1077.

Erdem T, Keane MP (1996) Decision-making under uncertainty: Capturing choice dynamics in turbulent consumer goods markets. *Marketing Sci.* 15(1):1–21.

Erdem T, Keane MP, Sun B (2008) A dynamic model of brand choice when price and advertising signal product quality. *Marketing Sci.* 27(6):1111–1125.

Fradkin A (2017) Search, matching, and the role of digital marketplace design in enabling trade: Evidence from Airbnb. Working paper, Boston University, Boston.

Gardete P, Antill M (2019) Guiding consumers through lemons and peaches: a dynamic model of search over multiple characteristics. Working paper, Nova School of Business and Economics, Lisbon, Portugal.

Ghose A, Ipeirotis P, Li B (2012) Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. *Marketing Sci.* 31(3):492–520.

Ghose A, Ipeirotis P, Li B (2014) Examining the impact of ranking on consumer behavior and search engine revenue. *Management Sci.* 60(7):1632–1654.

Ghose A, Ipeirotis P, Li B (2019) Modeling consumer footprints on search engines: An interplay with social media. *Management Sci.* 65(3):1363–1385.

Gittins J, Jones D (1974) A dynamic allocation index for the sequential design of experiments. Gani J, Sarkadi K, Vince I, eds. *Progress in Statistics* (North-Holland, Amsterdam), 241–266.

Gittins J (1979) Bandit processes and dynamic allocation indices. *J. Royal Statist. Soc.* 41(2):148–177.

Gittins J (1989) *Multiarmed Bandit Allocation Indices* (John Wiley & Sons, New York).

Hong H, Shum M (2006) Using price distributions to estimate search cost. *RAND J. Econom.* 37(2):257–275.

Honka E (2014) Quantifying search and switching costs in the U.S. auto insurance industry. *RAND J. Econom.* 45(4):847–884.

Honka E, Chintagunta P (2017) Simultaneous or sequential? Search strategies in the U.S. auto insurance industry. *Marketing Sci.* 36(1):21–42.

Hu M, Dang C, Chintagunta P (2019) Search and learning at a daily deals website. *Marketing Sci*. 38(4):609–642.

Jindal P, Aribarg A (2018) The value of price beliefs in consumer search. Working paper, UNC Kenan-Flagler Business School, Chapel Hill, NC.

Ke TT, Villas-Boas JM (2019) Optimal learning before choice. *J. Econom. Theory* 180(March):383–437.

Ke TT, Shen ZM, Villas-Boas JM (2016) Search for information on multiple products. *Management Sci.* 62(12):3576–3603.

Kim JB, Albuquerque P, Bronnenberg BJ (2010) Online demand under limited consumer search. *Marketing Sci.* 29(6):1001–1023.

Kim JB, Albuquerque P, Bronnenberg BJ (2017) The probit choice model under sequential search with an application to online retailing. *Management Sci.* 63(11):3911–3929.

Koulayev S (2013) Search with dirichlet priors: Estimation and implications for consumer demand. *J. Bus. Econom. Statist.* 31(2):226–239.

Koulayev S (2014) Search for differentiated products: identification and estimation. *RAND J. Econom.* 45(3):553–575.

Lai T (1987) Adaptive treatment allocation and the multiarmed bandit problem. *Ann. Statist.* 15(3):1091–1114.

Lin S, Zhang J, Hauser JR (2014) Learning from experience, simply. *Marketing Sci.* 34(1):1–19.

Ma L (2016) Only the interested learn: A model of proactive learning of product reviews. Working paper, Guanghua School of Management, Beijing.

McFadden D (1989) A method of simulating moments for estimation of discrete response models without numerical integration. *Econometrica* 57(5):995–1026.

Moraga-Gonzalez J, Wildenbeest M (2008) Maximum likelihood estimation of search cost. *Eur. Econom. Rev.* 52(5):820–848.

Moraga-Gonzalez JL, Sandor Z, Wildenbeest M (2015) Consumer search and prices in the automobile market. Working paper, VU University, Amsterdam.

Narayanan S, Manchanda P, Chintagunta P (2005) Temporal differences in the role of marketing communication in new product categories. *J. Marketing Res.* 42(3):278–290.

Rothschild M (1974) Searching for the lowest price when the distribution of prices is unknown. *J. Political Econom.* 82(4): 689–711.

Seiler S (2013) The impact of search costs on consumer behavior: a dynamic approach. *Quant. Marketing Econom.* 11(2):155–203.

Seiler S, Pinna F (2017) Estimating search benefits from path-tracking data: measurement and determinants. *Marketing Sci.* 36(4):565–589.

Stigler GJ (1961) The economics of information. *J. Political Econom.* 65(3):213–225.

Ursu R (2018) The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions. *Marketing Sci.* 37(4):530–552.

Weitzman M (1979) Optimal search for the best alternative. *Econometrica* 47(3):641–654.

Wu C, Che H, Chan T, Lu X (2015) The economic value of online reviews. *Marketing Sci.* 34(5):739–754.