Prior Information and Consumer Search: Evidence from Eye-tracking

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PRELIMINARY AND INCOMPLETE

Abstract

In many markets, consumers lack perfect information about all available options or their features before making a purchase decision. To understand consumer behavior in such markets, previous work has proposed models of consumer search, where consumers trade off the benefit against the cost of additional information and may therefore not acquire all the information available. Although rich, most of this literature has thus far focused solely on the role of consumer preferences and search cost in guiding search and purchase decisions. However, information acquired prior to beginning a current search, for example, that acquired through past purchases or uses of a given product, may also affect consumer decisions. In this paper, we develop a model of sequential search that additionally incorporates the impact of prior information on consumer search and purchase decisions. We estimate this model on a data set of consumers making smartphone search and purchase decisions. Our data set has two novel features: (i) it contains information on consumers’ prior ownership of and experience with the products; and (ii) it captures search behavior at the very granular level of eye-movements. Preliminary evidence from our data demonstrates the importance of prior information: the more familiar consumers are with a product, the more likely they are to search and purchase it. Using these data, we then quantify the impact of prior information, in addition to consumer preferences and search cost, as well as document the estimation bias arising from omitting prior information from the model. These results highlight the role of prior information in the consumer search process. As such, they may provide managers with additional insights when designing the environment in which consumers search to account for both consumers’ prior knowledge and current product information.

Keywords: consumer search, search with learning, prior uncertainty, eye-tracking.

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1 Introduction

In many markets, consumers lack perfect information about all available options or their features before making a purchase decision. For example, when searching for an auto-insurance policy, consumers check only 3 of more than 20 companies available before making a purchase (Honka, 2014). Also, when consumers shop for books, 75% of them only search one retailer (De los Santos et al., 2012), while in the digital camera category, 72% of a consumers’ search volume is concentrated at their most visited company (Bronnenberg et al., 2016).

To understand consumer behavior in such markets, previous work has proposed models of consumer search. These models follow either Weitzman (1979) or Stigler (1961), and describe consumer search behavior as the decision to trade off two primitives. One equals the consumer’s benefit from continuing search given revealed product characteristics, while the other is given by the cost of obtaining additional information. In such models, when the benefit from searching exceeds the cost, the consumer continues searching, and she stops and makes a purchase decision otherwise.\(^1\)

However, information acquired prior to beginning a current search, for example, that acquired through past purchases or uses of a given product, may also affect consumer decisions. As demonstrated by Moorthy et al. (1997) consumer prior knowledge of a product influences her search activity. Similarly, when modeling purchases, disentangling the effect of prior information from consumer preferences is important (Dubé et al., 2010, Shin et al., 2012). Yet, in previous work, no model of costly search exists that formalizes the effect of prior information.

In this paper, we develop a model of sequential search that additionally incorporates the impact of prior information on consumer search and purchase decisions. To incorporate the effect of prior information, we build on Ursu et al. (2019) and model consumer search as a learning process: consumers are uncertain about a product’s match value, but hold beliefs in the form of priors; by searching, they receive signals of this match value and update their beliefs in a Bayesian manner. In addition, our model also allows different product attributes to affect the variance of the signals that consumers receive. Finally, consumers are forward-looking and they use heuristics to make decisions, searching as if they have to make a purchase decision immediately after concluding the current search.

We estimate this model on a novel set of data on consumers making smartphone search and purchase decisions. These data are collected in collaboration with Analysis Group and Tobii Insight. Two features of these data stand out. First, they contain consumers’ prior

\(^1\)Extensive work in economics and marketing also studies to role of search costs on market outcomes, which is beyond the scope of this paper (e.g. Diamond (1971), Stigler (1961), Kuksov (2004) and for a review see Baye et al. (2006) and Anderson et al. (2018)).
information about the products. In particular, we observe the consumer’s prior brand ownership, familiarity with all brands, and experience using different product features. Second, in these data we observe consumer search decisions using eye-tracking methods. The 342 consumers in our data vary greatly in their prior ownership, with approximately 80% of consumers who own a smartphone, equally split among Apple, Samsung and other brands, and the rest who are planning to purchase their first smartphone. We also observe a large variation in consumers’ prior experience and familiarity with smartphones. In addition, from reduced-form analysis, we find that prior information helps explain observed search and purchase choices: consumers are more likely to search the brand they are familiar with, and subsequently more likely to purchase that brand.

In estimating the model, we find that prior information plays an important role in explaining consumer search behavior. More precisely, we show that prior ownership increases consumers’ evaluation of the product before beginning search; we also show that familiarity with a brand decreases the prior variance; and finally, product attributes that the consumer is more experienced in using provide more precise signals of her match value. In addition, we document the estimation bias arising from omitting prior information from the model. We find that estimated search costs are biased downwards, that the consumer preference for brands with high market share is overestimated, and that the signal variance for various product attributes is less precise.

These results highlight the role of prior information in the consumer search process. As such, they may provide managers with additional insights when designing the environment in which consumers search to account for both consumers’ prior knowledge and current product information.

The following section will first discuss the relevant literature and our contribution to the literature. Then we will introduce the data and present some preliminary reduced form evidence of the importance of prior information. In section 5, we introduce the model we use, followed by estimation results. The last section concludes.

2 Literature review

This paper contributes to two streams of the literature: (i) prior work modeling consumer search, and (ii) previous papers using eye-tracking data to analyze consumer decisions. In what follows, we describe our contributions to each of these streams.

First, we build on and contribute to prior work on models of costly search. This literature can be divided into groups of studies that focus on two different search methods: simultaneous and sequential search. Simultaneous search models assume that before search-
ing, consumers pick a set of options to become informed about, then search all of them, and finally make a purchase decision (Stigler, 1961). In contrast, in a sequential search model, the information consumers gather through search is taken into consideration when searching for the next option (Weitzman, 1979). In this paper, we collect consumers’ search decisions on a very granular level, observing how different information accumulated through search affects future decisions. Thus, we use the sequential search method to better account for consumers’ search behavior.

In addition, work on consumer search also distinguishes between what information consumers search for. One assumption in the search literature is that consumers are searching for a single attribute of the product, such as the price of the product (e.g., Hortacsu & Syverson, 2004, Honka & Chintagunta, 2016, De los Santos et al., 2012, Mehta et al., 2003) or for multiple attributes (Gardete et al., 2019 and Branco et al., 2015). Another assumption is that, in a differentiated product market, consumers can be searching for the match value of the product (Wolinsky, 1986, Kim et al., 2010, Kim et al., 2017, Moraga-Gonzalez et al., 2017). Finally, consumers may also search to learn the distribution of utility rewards, such as the distribution of the price or the match value (e.g., Rothschild et al., 1974 and De Los Santos et al., 2017). We build upon previous literature by modeling consumers search to uncover the match value for each brand, while we also allow product attributes to have a different impact on consumers search decisions.

Most of the prior studies on consumer search assume that consumers are able to resolve all the uncertainty about a product or its attributes through just one search. However, empirically, we often observe consumers revisit previously-searched information (Bronnenberg et al., 2016). To rationalize this pattern, some studies relax that assumption and allow consumers to gradually learn through search (Branco et al., 2015, Branco et al., 2012, Chick et al., 2012, Dukes et al., 2015, Ma, 2019, Ke, Shen, et al., 2016, Ke & Villas-Boas, 2019, Gardete et al., 2019, Ursu et al., 2019). In parallel, when studying consumers’ repeated purchase decisions, researchers also allow consumers to learn from previous purchases and update their beliefs under Bayesian learning framework (e.g., Erdem & Keane, 1996, Ackering, 2001, Ching et al., 2013 and Iyengar et al., 2007).

A key aspect of modeling consumer learning through purchase decisions is to disentangle the effect of prior information from consumer preferences (Dubé et al., 2010, Shin et al., 2012). Also, prior work provides reduced-form evidence of the effect of prior information on search (Moorthy et al., 1997, Honka, 2014 , Hortacsu, Madanizadeh, et al., 2017). Mostly closely related to our work is Moorthy et al. (1997), which finds an inverted-U-shaped relationship between search activity and consumer prior brand perceptions. However, no formal treatment of the effect of prior information in a sequential search model exists, which is the
focus of our paper.

Finally, another stream of the consumer search literature to which our work relates concerns the optimality of the search decisions. Some researchers assumed that consumers are fully rational and they make choices based on optimal decision rules (e.g., Weitzman, 1979 and P. B. Morgan, 1983). In contrast, consumers are found to use heuristics and rely on ‘fast and frugal’ approaches (e.g., Gabaix & D. I. Laibson, 2000 and Hauser, 2014). Models with heuristics built-in are also shown to fit the data better, perhaps because they more closely mimic the limited capacity of the brain (Swait et al., 2001). Similarly, models with forward-looking agents that take into account only one or two step ahead decisions are found to fit the data better than those accounting for all future decisions (Camerer et al., 2004). In line with these results, models of bounded rationality, such as the directed cognition (DC) model of Gabaix, D. Laibson, et al. (2006), are found to explain the data well in the setting where consumers need to acquire information before making a purchase. Yang et al. (2015) applied this model to a conjoint analysis where they observe consumers eye-movement, which is similar to our setting. Consumers are modeled to make search decisions as if they will make a purchase choice immediately after acquiring this new piece of information. It has been shown to perform better than a search model with optimal strategy rule. Tehrani et al. (2019) generalized the DC model to develop a heuristic rule, also referred to value of perfect information (VPI), that explains how consumers make a trade-off between exploration value and exploitation value. Its main idea is that information is only valuable if it can change the decision. This VPI rule has been tested to outperform optimal and index rules in computation time and model performance. Models with VPI is also shown to have comparable overall performance as the near-optimal approach. We will extend the literature by combining the decision rules and heuristics developed in Yang et al. (2015) and Tehrani et al. (2019) to allow consumers use heuristics and be forward-looking in their decision-making.

Lastly, our paper also bridges the literature on consumer search and eye-tracking. Eye-tracking has gained a lot of attention among researchers studying the computational processes of decision making (e.g., Wedel et al., 2008, Chandon et al., 2002). Eye-fixations, that is areas on which consumers hold a stable gaze lasting for more than 200 milliseconds, have been shown to be an indicator of attention on certain area-of-interest (Wedel et al., 2000). Eye-fixations also increase the memory of the fixated object (Pieters, Warlop, et al., 2002). Studies have modeled eye-fixation as endogenous choices to acquire information (Yang et al., 2015 and Shi et al., 2013). A recent paper using the same eye-tracking data as this paper, Pieters, Erdem, et al. (2019), finds that eye trajectories predict final product choices, and consumers pay more attention to the chosen products. Studies also found that heuristics in decision-making can lead to distinct patterns of eye-movement (Orquin et al.,
2013). Some researchers also advocate the use of Bayesian methods in building models that closely examines the processes from eye-tracking data (e.g., Wedel et al., 2008). Building upon the previous literature using eye-tracking data, we propose and estimate a structural sequential search model that explains how consumers make search and purchase decisions using heuristics and Bayesian updating.

In the following section, we introduce our data and present summary statistics and descriptive analysis.

3 Data

3.1 Study Design

We collected the data used in this study in 2013 in collaboration with Analysis Group and Tobii Insight\(^2\), an eye-tracking and marketing research firm, for the purposes of a litigation case. The experiment mimics a common shopping experience on smartphone online stores where consumers examine a limited set of products and choose which one to purchase. Specifically, the consumers in the experiment were asked to perform a product comparison task in which they evaluate 5 smartphones intending to choose one to purchase. The consumers in this study are recruited from Tobii’s partner organization’s database from three cities, San Diego, Cincinnati, and Washington DC. The three partner organizations are Luth Research (San Diego), Various View Research (Cincinnati) and Shugoll Research (Washington DC). The consumers must be at least 18 years old and did not have eye problems, such as nystagmus. The recruited consumers must not work for a research company, advertising agency or technology company such as Apple. Consumers were required to own a cell phone at the time of participation and were intending to purchase a smartphone within 9 months. There are 4 major segments of consumers in the population: 1) Apple owners; 2) Samsung owners; 3) Other brand owners; 4) non-smartphone owners. To ensure the representation of consumers in our study, We applied stratified sampling method to draw equal amount of consumers from each of these 4 segments. The recruited consumers are scheduled to visit the research facilities and they are offered $50 to cover the transportation costs and their time.

There are in total 5 products under the comparison, including Apple iPhone and Samsung Galaxy. The determination of the phones used in the design was guided by the top 20 Google search results for various keywords such as ‘best top smartphone 2013’. The five smartphones we used are also commonly mentioned in the review reports. The attribute

\(^2\)https://www.tobiipro.com/insight/
was informed by the common availability of the attributes featured on retailer websites. The information is extracted from 1) major four carriers websites including ATT, Verizon, Sprint and Tmobile; 2) top four retailers including Amazon, Bestbuy, Target mobile and Walmart; 3) top independent review sites such as Verge, CNET, PCWorld and gdgt.com. The attributes that we use in the study here is determined by the common availability of the attributes and features on these websites.

Previous literature suggested that the choice complexity impact how consumers acquire and process information (Swait et al., 2001). Payne (1976) has found that consumers use different information processing strategies when they face different levels of choice complexity. Choice complexity is often manipulated by the varying number of attributes or number of options available to consumers (Malhotra, 1982). In our context, the number of attributes that were shown to consumers is operationalized to test the effects of decision complexity. There are 3 conditions of decision complexity, low (18 attributes), medium (29 attributes), and high (39 attributes). The figure 1 displayed the options that consumers see in the low complexity condition. From top to bottom, attributes that consumers see on this figure can be categorized as Brand (including a photo of the product and color option), Price, Wireless Capabilities, OS system, Size, Display, Battery, Camera, and Memory. All three complexity conditions have these parent attribute categories. The number of attributes that nest within these categories varies from condition to condition. For example, while there is just 1 attribute under ‘Camera’ in low complexity condition, there are 3 attributes under ‘Camera’ in high condition. For the ease of analysis, we combined the ‘Display’ and ‘Size’ into one as ‘Size’. We will also combine the ‘Wireless Capabilities’ and ‘OS system’ into one as ‘Technical’. In total, we have 7 main categories of attributes in our analysis: Brand, Price, Camera, Battery, Size, Technical and Memory.

The order of the brand and attributes displayed on the screen is rotated to control for the order effect. Under each of the 3 complexity conditions, there are 5 unique combinations of attribute and brand orders. In total, these 15 unique stimulus were randomized across subjects. Consumers are asked to make only one purchase decision and they can take however much time they need to make that decision. There’s a ‘Click to buy’ button on each of the option and once a consumer click on that button, a confirmation page will pop out and ask them to confirm the choice.
Consumers are also asked to fill out a survey before the task about their prior information. They answered questions such as:

1. Do you currently own a smartphone or not?
2. What is the current model or brand of the smartphone you own?
3. How familiar are you with the brands in the experiment (1 to 7 scale)?
4. How much do you use each of the functions of the smartphone: video taking, photo taking, internet browsing, video chatting, texting, calling, etc.?

We also gathered information on consumers’ age, income, gender and employment status. There are in total 460 consumers who participated in the experiment but there are a few who failed to complete the task. In the end, we have 342 consumers for who we observe complete set of eye-movement data, complete demographic and prior information. The eye-movement data of these 342 consumers are output as AOI (area of interest) hit matrix by Tobii. These data are generated using standard settings in the eye-tracking software.

### 3.2 Summary Statistics

In this section, we will present some summary statistics about our data. In total, we have 342 consumers and 78,275 observations. The majority of the consumers in our data is in the age group of 30 to 49. Among the 342 consumers, 52% are female, 69% are white and 71% are employed. Around 56% of the consumers have an annual income of over $50,000. According to the table 1, each consumers on average make about 278 fixations. They are required to make only one purchase choice in the task. Over 70% of the consumers in our
data already have a smartphone. In conclusion, our consumers on average know moderately about smartphone and they are interested in making a purchase at the time when the study is carried.

Table 1: Summary Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Consumers</td>
<td>342</td>
</tr>
<tr>
<td>Total Number of Fixations</td>
<td>78,275</td>
</tr>
<tr>
<td>Average Number of Fixations per Consumers</td>
<td>278</td>
</tr>
<tr>
<td>Percentage of consumers with smartphone</td>
<td>72%</td>
</tr>
</tbody>
</table>

We observe a lot of variation in consumers prior experiences with smartphones. Table 2 and 3 reports consumers previous ownership, familiarity and the experiences with smartphones, which are the key variables in our model that identifies the consumers’ prior uncertainty. First, the table 2 summarizes consumers’ prior ownership and familiarity with each of the five brands in the study. Apple and Samsung are the two most popular smartphone brands amongst our consumers in terms of previous ownership and purchase choice. Interestingly, even though HTC is the second least familiar brand to consumers, after searching, 21% of the consumers chose to purchase HTC, second to Apple. The least popular brand for the smartphone among our consumers is Nokia.

Table 2: Previous Product Ownership, Familiarity and Final Purchase Choice

<table>
<thead>
<tr>
<th>Brand</th>
<th>Previously Own%</th>
<th>Average Familiarity</th>
<th>Purchase Choice%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>29.53</td>
<td>4.757</td>
<td>25.73</td>
</tr>
<tr>
<td>Samsung</td>
<td>24.27</td>
<td>4.196</td>
<td>29.24</td>
</tr>
<tr>
<td>HTC</td>
<td>11.11</td>
<td>2.880</td>
<td>21.34</td>
</tr>
<tr>
<td>Moto</td>
<td>6.43</td>
<td>3.108</td>
<td>16.08</td>
</tr>
<tr>
<td>Nokia</td>
<td>0.58</td>
<td>2.406</td>
<td>7.60</td>
</tr>
<tr>
<td>Others</td>
<td>7.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>20.76</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Second, table 3 summarizes the consumers’ experiences with smartphones, which are measured by how much consumers have used smartphone functions such as video-taking, photo-taking, internet-browsing. There are in total 16 functions we asked consumers about in the survey, which we trace back to these 5 major product attributes: Camera, Battery, Size, Technical and Memory. Note that since consumers do not directly interact with the ‘Brand’ and ‘Price’, we do not have measurements for their experiences with these 2 product attributes. The measurement of consumers’ experiences ranges from 0 to 1, where 0 stands
for ‘never’ and 1 stands for ‘several times per day’. It can be seen from table 3, there’s a large variation in the level of experiences with these functions. Consumers in our data on average are most experienced with the ‘Battery’ attribute (0.706) and the least experienced with the ‘Technical’ and ‘Camera’ attribute. The functions correspond to ‘Battery’ is voice-calling, texting, and video-chatting, which is related to the essential communication function of the phone. The functions that correspond to ‘Camera’ are photo and video-taking. In 2013 when we collected the data, cameras in smartphones were not as attractive as they are, and photo-taking and video-taking was still a new experience to most users. There is also a large variation across consumers as can be seen from the standard deviations.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Pctl(75)</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical</td>
<td>342</td>
<td>0.447</td>
<td>0.281</td>
<td>0</td>
<td>0.3</td>
<td>0.7</td>
<td>1</td>
</tr>
<tr>
<td>Size</td>
<td>342</td>
<td>0.500</td>
<td>0.339</td>
<td>0</td>
<td>0.2</td>
<td>0.8</td>
<td>1</td>
</tr>
<tr>
<td>Battery</td>
<td>342</td>
<td>0.706</td>
<td>0.409</td>
<td>0</td>
<td>0.4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Camera</td>
<td>342</td>
<td>0.446</td>
<td>0.309</td>
<td>0</td>
<td>0.2</td>
<td>0.7</td>
<td>1</td>
</tr>
<tr>
<td>Memory</td>
<td>342</td>
<td>0.529</td>
<td>0.358</td>
<td>0</td>
<td>0.1</td>
<td>0.8</td>
<td>1</td>
</tr>
</tbody>
</table>

Next, we will take a look at the distribution of the consumers’ purchase choice with regards to the product they own. The figure 3.2 plots the distribution of consumers with their previously owned product and their purchase decision they make at the end of the study.

The y-axis plots the brands that consumers previously owned. In the survey before study, when consumers were asked about their previous product ownership, they are allowed to choose any of the 5 brands that we already include in our task, plus ‘none’ for consumers who do not have smartphones and ‘others’ for consumers who have brands that are not included in the task. The x-axis plots the brands that consumers decided to choose at the end of the task. The size and color of the bubble indicate the number of consumers. The bigger the bubble, the more consumers. As can be seen clearly, there’s a group of consumers who are loyal to their previously owned brand. It is noted that among people who do not have a smartphone (as the bubbles in the ‘Owned: None’ row on the top), Apple, HTC and Samsung have similar market share in their final purchase choices. We refer to the consumers who stick to their previously owned brand as ‘loyal consumers’, and the ones who don’t as ‘switchers’. For consumers who do not have a smartphone or have a smartphone of other brands, they are categorized as ‘switchers’ as well. The figure 3 summarizes the distribution of fixations for loyal and switchers among five brands.
The y-axis again denotes the brands that consumers previously own. The x-axis denotes the 5 brands in our setting. The size and color of the bubble indicate the share of fixations to these 5 brands on the x-axis. As can be seen from the top half of the figure 3, there’s a strong trend along the diagonal: loyal consumers contribute most of their fixations to the brand they are loyal to. However, for switchers, the distribution of the fixations do not have a strong diagonal trend. On average, Samsung and HTC draw more fixations compared to other brands. It can be seen that the allocation of fixations, or namely search in our context, is closely related to the choice.

4 Reduced Form Evidence

To motivate our model, we present some reduced-form evidence. These analysis can also help us understand the data better. First, we want to know how does prior information impact consumers’ search choices. Do consumers start with the brands they already own or the
brand they are least familiar with? To answer this question, we summarize the percentage of consumers’ fixations to each of the brands, split by brands that consumers previously own and brands that consumers do not previously own. Figure 4 reports the analysis. The left half of the figure reports the share of fixation out of the first 10 fixations while the right half reports the share for all the fixations. The y-axis denotes the percentage of the fixations out of all fixations, averaged across consumers. As can be seen, through both the early stage of the search and the whole search, consumers pay more fixations to products they previously own.

![Figure 4: Distribution of Fixations by Brand](image)

To analyze how prior information impact consumers purchase decisions, we run a conditional logit model with consumers’ purchase choice the dependent variable:

\[ U_{ij} = p_{oi} + brand_j + fam_{ij} + fixations_{ij} \]

The utility \( U_{ij} \) is a function of previous ownership of the brand, \( p_{oi} \), familiarity with the brand, \( fam_{ij} \) and the number of fixations accumulated to each of the 5 brands during the experiment, \( fixations_{ij} \). The results are presented in the table 4. The model (1) is a baseline model which does not include prior information (previous ownership and familiarity), while model (2) includes prior information but not fixations. As can be seen, the previous ownership and familiarity improves the model fit and they both have a positive and significant coefficient, suggesting that consumers are more likely to purchase the product they own and are familiar with, controlling for their searches. Second, the fixations by brand has positive and significant coefficient too, suggesting that the eye fixation allocated to the brand can
also explain the final choice. Noted that in the model (3), it can be seen that the brand intercepts are no longer significant after the fixation is added to the model.

Table 4: Prior Information on Consumers’ Purchase Choice

<table>
<thead>
<tr>
<th>Purchase Choice</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous Ownership</td>
<td>0.841***</td>
<td>0.866***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.161)</td>
<td>(0.212)</td>
<td></td>
</tr>
<tr>
<td>brand: apple</td>
<td>1.595***</td>
<td>0.234</td>
<td>0.421</td>
</tr>
<tr>
<td></td>
<td>(0.293)</td>
<td>(0.338)</td>
<td>(0.445)</td>
</tr>
<tr>
<td>brand: htc</td>
<td>1.331***</td>
<td>0.877***</td>
<td>0.327</td>
</tr>
<tr>
<td></td>
<td>(0.300)</td>
<td>(0.313)</td>
<td>(0.431)</td>
</tr>
<tr>
<td>brand: samsung</td>
<td>1.705***</td>
<td>0.684**</td>
<td>0.262</td>
</tr>
<tr>
<td></td>
<td>(0.291)</td>
<td>(0.316)</td>
<td>(0.425)</td>
</tr>
<tr>
<td>brand: moto</td>
<td>0.857***</td>
<td>0.441</td>
<td>0.246</td>
</tr>
<tr>
<td></td>
<td>(0.319)</td>
<td>(0.331)</td>
<td>(0.462)</td>
</tr>
<tr>
<td>Familiarity</td>
<td>0.342***</td>
<td>0.394***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.080)</td>
<td></td>
</tr>
<tr>
<td>Fixation</td>
<td>0.076***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,230</td>
<td>1,230</td>
<td>1,230</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−364.928</td>
<td>−306.109</td>
<td>−165.634</td>
</tr>
</tbody>
</table>

*Note: *p<0.1; **p<0.05; ***p<0.01

Given the results from the reduced form models, we can see that consumers are more likely to search and purchase a brand when they own the brand or are familiar with the brand. Our analysis suggests that it’s important to calibrate search models on prior information. The next section will explain in detail how we build a model that can use consumer prior information to explain search and purchase choices.

5 Model

In this section, we present the structural model that we use to model consumer search and purchase choices. Figure 5 below presents a diagram that helps to illustrate how consumers make decisions in our setting. In our model, consumers are modeled to learn with the Bayesian updating rule. At time t=0 (on the left of the figure), a consumer start the search with a prior uncertainty, also referred to as the prior belief in traditional Bayesian learning models (e.g., Erdem, Keane, et al., 2005). The consumer can choose to search the options and pay a search cost, or end the search to purchase one of the options. The number of search
options available to the consumer at any given time t is $j^l$, where j denotes the product and l denotes the attributes. If the consumers choose to search, product 1 and attribute 2 for instance, the consumer will fixate on product 1 and attribute. A signal will be drawn, and the consumer’s beliefs about product 1 will be updated. At time $t=1$, the updated consumer’s beliefs will become the priors, and the consumer will need to make the search or purchase choice again. This repeats until the consumer make a purchase choice.

Figure 5: How Consumers Make Search and Purchase Decisions

In our model, first, at time $t=0$, the consumers have prior beliefs about products $j$, which follows a normal distribution:

$$\mu_{ij,t=0} \sim N(\bar{\mu}_{ij,t=0}, \delta_{ij,t=0})$$  \hspace{1cm} (1)

where the prior mean is a function of previous ownership and the prior variance is a function of the consumer i’s familiarity with product $j$.

$$\bar{\mu}_{ij,t=0} = \theta_0 + \theta_1 \ast po_{ij}$$  \hspace{1cm} (2)

$$\delta_{ij,t=0} = exp(w_1 \ast fam_{ij})$$  \hspace{1cm} (3)

The signal $s_{ij}^l$ that consumers will receive from searching product $j$ and attribute $l$ also follows normal distribution:

$$s_{ij}^l \sim N(S_j, \sigma_{ij}^l)$$  \hspace{1cm} (4)

where the mean of the signal for each brand is the $\theta_j$. The variance of the signal is a
function of users’ experiences with attributes, \( exp^l_i \), attribute intercepts, \( \delta_0^l \) and complexity level \( \delta_c \). The \( \delta_0^l \) captures the effect of prior experiences with attributes. The \( \delta_0^l \) explains why some attributes are intrinsically more informative than others. As previously discussed, we manipulate the choice complexity in our setting by providing a different amount of attributes information to consumers. The parameter \( \delta_c \) here captures the effect complexity on consumers’ signal variance.

\[
\bar{S}_j = \theta_j 
\]

\[
\sigma^l_{ij} = exp(\delta_0^l + \delta_c + \delta_s \ast exp^l_i) 
\]  

(6)

When consumer search the product \( j \) and attribute \( l \), a signal will be drawn, \( s^l_{ij} \). The update of the priors and variance follows the standard Bayesian updating rules:

\[
\delta^l_{ij,t+1} = \frac{1}{\delta^l_{ij,t} + \sigma_{ij}^l} 
\]

(7)

\[
\mu_{ij} = \frac{\mu_{ij,t-1} + s^l_{ij}}{\delta^l_{ij,t-1} + \sigma_{ij}^l} 
\]

(8)

As previous discussed, we follow the decision rule in Yang et al. (2015) where consumers search as if they have to make a decision right after the immediate search. Thus, consumers make choices between:

- Purchase the product \( j \) and receive:

\[
EU_{ij,t} = \mu_{ij,t} - r \ast \mu_{ij,t} - r \ast \delta^2_{ij,t} + \epsilon_{ijt} 
\]

(9)

- Search product \( j \) and attribute \( l \) and receive

\[
EU^l_{ij,t+1} = \mu_{ij,t} - r \ast \mu_{ij,t} - r \ast \delta^2_{ij,t+1} + VPI^l_{ij,t} - sc_{ijt} + \epsilon^l_{ijt} 
\]

(10)

where the \( r \) stands for the risk coefficient, and the error term \( \epsilon_{ijt} \) follows generalized extreme value distribution. The \( VPI \) stands for the value of perfect information as in Tehrani et al. (2019). It is computed empirically by ranking options, and then compute an integration of a truncated distribution. In our model, VPI is product and attribute specific. In this example here, we will discuss a simple case for calculating VPI. For the ease of notation, we ignore the subscript for the attribute.  

16
• Assume there are consumer i and option j. At time t, the k is the best option and \( V_{ijt} \) is the expected utility of that option j at time t;

• D stands for the number of draws;

• For the inferior option, the VPI is calculated by comparing the draws with the best option:

\[
VPI_{ijt} = \frac{1}{D} I(V_{ijt}^D > V_{ikt})[V_{ijt}^D - V_{ikt}]
\]

where \( V_{ikt} \) is the best option and \( I() \) is an indicator function

• For the best option, compare the draws with the second best option:

\[
VPI_{ijt} = \frac{1}{D} I(V_{ijt}^D < V_{igt})[V_{igt}^D - V_{ijt}]
\]

where \( V_{igt} \) is the second best option.

The VPI will decrease for searched options over time. For options with high variance, the VPI will also be high.

If consumers decide to keep searching, they also need to pay the search cost. The search cost follows:

\[
sc_{it} = \exp(sc_0 + d_1(\triangle l_i) + d_2(\triangle j_i) + d_3 \times l_{loc} + d_4 \times j_{loc} + \eta \times wsp_i + sc_i \times demo_i) \quad (11)
\]

where the \( sc_0 \) is a constant and the \( (\triangle l_i) \) and \( (\triangle j_i) \) denotes the standardized distance from current fixation location to any other possible fixation location. It ranges from 0 to 1, and 1 stands for the farthest possible fixation location on the screen. The \( (\triangle l_i) \) denotes the distance in attribute level, namely the row-level; while \( (\triangle j_i) \) denotes the distance at the brand level, namely the column level. The \( l_{loc} \) and \( j_{loc} \) controls for the absolute position of each attribute and brand on the screen. Yang et al. (2015) analyzed the search action and suggested that people are more likely to move their eyes to contiguous cells in a product matrix setup because when cells are distant, it is more cognitively costly for eye movement. We also observe such patterns in the data. The \( wsp_i \) is the percentage of fixations that consumers paid to the white-space area on the screen. Because there’s no information on the white-space area on the screen, the \( wsp_i \) can potentially explains how much does time value to consumers during the study given that search is costly. The \( demo_i \) captures consumers’ demographics such as age, gender, and income. Previous literature found that search cost are related to observed consumer characteristics, such as income and age (De Los Santos
et al., 2017 and De los Santos, 2018). Individuals with higher incomes are more likely to have higher search cost.

In our paper, given that we have 5 brands and 7 attributes, the consumers can choose from 35 different possible brand-attribute combinations to search. At each time t, we will calculate the VPI for these 35 options to obtain the value of exploration of these options. Meanwhile, each consumer has 5 purchase options. Combining these search and purchase options, at any given time, the consumers need to choose 1 option out of 40 options. However, simply modeling consumers as picking one out of 40 options will suggest the same substitution pattern exists among search and purchase choices. In reality, this might not be the case. Thus, we model the search and purchase choices as two nests of choices to allow the correlation in error term within nests. Assuming the σ captures the within-group correlation in error terms between purchase choices, for the consumers i to choose to keep searching brand j and attribute l, the probability follows:

\[
\text{Prob}(\text{Search} = jl) = \frac{V_{\text{search}}^i}{V_{\text{search}}^i + V_{\text{buy}}^i \sum_j \exp(EU_{ij,t+1}^l)} \sum_j \exp(EU_{ij,t+1}^l) \\
\]

and

\[
V_{\text{search}}^i = \sum_j \exp(EU_{ij,t+1}^l) \\
V_{\text{buy}}^i = (\sum_j \exp(EU_{ij,t+1}^l))^\sigma 
\]

There are three parameters in our model that describes the effects of prior uncertainty. First, the \( \theta_1 \) indicates us about how the previous ownership impacts consumers’ prior preferences. Second, the \( w_1 \) indicates the impact of the familiarity with brands on the initial variance of the belief in the search. Third, the \( \delta_s \) explains whether the experiences with certain functions of the phone will make that attribute more diagnostic or not. These parameters tell us about the power of prior uncertainty on search.

5.1 Identification

In this section, we will discuss our model’s identification. First, the consumers who do not have a smartphone will help us to identify the \( \theta_0 \) and \( \delta_0 \). The \( \theta_0 \) is the constant in the prior mean, which indicates the starting state of consumers who do not own a smartphone. The signal mean intercepts, \( \delta_0 \), controls for the intrinsic variance associated with each of the attributes. It will capture the effects that consumers, on average, find an attribute more informative than others, regardless of their experiences with the attribute. The preferences
for each brand will be identified from the search and purchase choices.

The search cost will be identified from the choice of stopping search. From equation 10, we can see that when the utility of exploring decreases to a degree that the benefit of continuing search is no longer higher than the search cost, consumers will stop. The number of fixations will help to identify the range of the search cost while the function form of the search cost can help to pin down the exact level. As consumers search, the uncertainty will steadily decrease but the search cost will remain the same. Holding the uncertainty level constant, higher search cost will lead consumers to search less in general. As previously discussed, the order of the brand and attribute that is displayed on the screen is randomized across subjects. This will help us to identify the parameters that control for location and order effects in the search cost. In the end, the demographics and white-space will also help us to identify search cost.

5.2 Monte Carlo Simulation

To test our model, we simulated the eye-fixation and purchase data using pre-fixed parameters. We generated 1000 consumers with their previous brand ownership, familiarity with 5 brands and their experiences with the 7 attributes. The simulation model is a simplified version of the model we used for estimation but it keeps all the key parameters. In the simulation, consumers follow the same decision rule and heuristics as in our main estimation. The estimation results for the parameters are reported in table 5.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>True</th>
<th>Estimate</th>
<th>Std.Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior Mean: Constant</td>
<td>-2.00</td>
<td>-2.24</td>
<td>0.04</td>
</tr>
<tr>
<td>Prior Mean: Previous Ownership</td>
<td>1.00</td>
<td>1.23</td>
<td>0.03</td>
</tr>
<tr>
<td>Prior Variance/Familiarity</td>
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<td>-0.38</td>
<td>0.02</td>
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<tr>
<td>Signal Mean: Match Value</td>
<td>2.00</td>
<td>1.91</td>
<td>0.06</td>
</tr>
<tr>
<td>Signal Variance/Experience</td>
<td>-1.00</td>
<td>-1.37</td>
<td>0.10</td>
</tr>
<tr>
<td>White-space</td>
<td>-1.00</td>
<td>-0.44</td>
<td>0.12</td>
</tr>
<tr>
<td>Search Cost Constant</td>
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<td>-1.16</td>
<td>0.04</td>
</tr>
<tr>
<td>Risk</td>
<td>1.00</td>
<td>1.03</td>
<td>0.05</td>
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<tr>
<td>Within-nest Correlation: Purchase</td>
<td>0.60</td>
<td>0.42</td>
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</tr>
<tr>
<td>Log-Likelihood</td>
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<td></td>
<td>-17736.8</td>
</tr>
</tbody>
</table>

As can be seen, our model can recover the true parameters. The next section will present
6 Estimation Results

We estimate the model with the data of 342 consumers. In total, we have 78,275 observations including both search and purchase decisions. In this section we present the maximum likelihood estimation for the model in table 6. We also estimated a variation of the model without the data on prior information (prior uncertainty parameters fixed at zero), which implies that consumers share the same prior belief, same as the setting in Ursu et al. (2019). The left two columns report the estimation of the model that is estimated with data on prior information.

First, the top section of the table reports the estimation of the parameters in the prior mean and prior variance. It can be seen that the parameter for previous ownership is significant and positive, suggesting that consumers prior utility for previously-owned brand is higher compared to other brands. This confirms the findings from Honka (2014), which also find previous ownership to have positive effects on consumers’ utility. The parameter for prior variance, familiarity, is negative, which indicates that consumers have more accurate priors (lower variance), for brands that they are familiar with. Comparing the two models, it can be seen that the constant in the prior mean is positive in both model but the magnitude is much higher when the model is estimated without data on prior information (0.327 compared to 0.193). This suggests that when we do not count for the preference due to previous-ownership, we can over-estimate the preferences for smartphone.

Next, the second section of the table reports the estimates of match value. In our model, match value is modelled as the mean level of the signals that consumers receive from each brand. It is estimated with Nokia standardized to zero. Comparing the two models, one estimated with data on prior information and one without, though Apple is always the brand with the highest match value, the rank of the match value between other four brands changes. In the model estimated with prior data, HTC is higher than Samsung but in the model without prior, it is the opposite. As previously discussed, though HTC was not the brand that has the highest prior market share, many consumers chose HTC as the brand to purchase. In fact, in our data, among consumers who are not loyal to their previous brands, HTC is the most popular brand for purchase. The model without prior ignores this information so the preference estimation for the brands is biased.

The third section presents the estimates of the parameters in the signal variance. The coefficient for consumers’ experiences with product functions is negative, suggesting that when consumers have more experience with certain product attributes, they receive more
precise signals from these attributes. As we comparing the intercepts for attributes from the model that is estimated with data on prior information, it can be seen that brand and technology have the lowest constants (-0.514 and -0.269 respectively), which indicate that they are the least noisy signals on average. The parameters in the signal variance that denotes the effects of the medium and high complexity levels are both positive. It suggests that choice complexity increases the uncertainty that consumers need to resolve in search. It can be seen that the estimates change drastically when we do not include the data on prior information, indicating that we will likely have a biased estimates of the diagnostic value of the attributes when we do not consider prior uncertainty.

The last section of the table 6 reports the estimation results of parameters in search costs. First, we examine the results for the model with prior uncertainty. The parameters that controls for the absolute distance between search options on the screen, ‘Distance: attribute’ and ‘Distance: attribute’, are both positive, suggesting that consumers are more likely to move their eyes to the information that is close to that they are searching currently. This confirms the findings from Yang et al. (2015), and also consistent with the data patterns we observed in the data. The parameter for the ratio of fixations on white-space is negative, which suggests that consumers who fixated more on white-space have lower search cost. We can also see that female, older, employed and high-income consumers have higher search cost. Comparing these parameters across two models, we can see the overall magnitude of search cost decreases when we do not include the data on prior information. Given the setting in our model, when we remove the prior information from the model, consumers will start with a higher uncertainty. Thus, search cost will decrease in order for the model to explain the observed search pattern. Additionally, it’s likely that consumers’ demographics are correlated with their prior information. Without adequately counting for the prior information, we will likely get biased estimates on search costs.

Our results highlight the importance to consider prior experiences in modeling consumers’ search and purchase decisions. To compare the goodness-of-fit, we also report the Log-likelihood, AIC and BIC here. It is clear that the model estimated with prior uncertainty fits the data better than the model without.
<table>
<thead>
<tr>
<th></th>
<th>With Prior</th>
<th></th>
<th>Without Prior</th>
<th></th>
</tr>
</thead>
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<tr>
<td></td>
<td>Estimate</td>
<td>Std.Error</td>
<td>Estimate</td>
<td>Std.Error</td>
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<tr>
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<td>0.039</td>
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<td>Constant</td>
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<td>0.019</td>
<td>0.327</td>
<td>0.039</td>
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<td>0.019</td>
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<tr>
<td><strong>Signal Mean/Match Value</strong></td>
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<td></td>
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<tr>
<td>Apple</td>
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<td>0.025</td>
<td>0.497</td>
<td>0.014</td>
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<td>HTC</td>
<td>0.385</td>
<td>0.024</td>
<td>0.384</td>
<td>0.016</td>
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<td>0.024</td>
<td>0.384</td>
<td>0.016</td>
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<td>0.06</td>
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<td>0.039</td>
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<td>-0.150</td>
<td>0.039</td>
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<td>0.059</td>
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<td>0.062</td>
<td>-0.140</td>
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<td>Size</td>
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<td>0.063</td>
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<tr>
<td>Battery</td>
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<td>0.092</td>
<td>0.002</td>
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<tr>
<td>Camera</td>
<td>0.068</td>
<td>0.088</td>
<td>-0.087</td>
<td>0.049</td>
</tr>
<tr>
<td>Memory</td>
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<td>0.069</td>
<td>-0.110</td>
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<tr>
<td>Medium Complexity</td>
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<td>High Complexity</td>
<td>0.964</td>
<td>0.039</td>
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<td><strong>Search Costs</strong></td>
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<td></td>
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<tr>
<td>White-space</td>
<td>-3.277</td>
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<td>Distance: attribute</td>
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<td>1.473</td>
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</tr>
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<td>0.019</td>
<td>1.276</td>
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<td>-0.196</td>
<td>0.017</td>
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<td>0.024</td>
<td>-0.211</td>
<td>0.021</td>
</tr>
<tr>
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<td>0.118</td>
<td>0.027</td>
<td>0.071</td>
<td>0.022</td>
</tr>
<tr>
<td>Age</td>
<td>0.143</td>
<td>0.015</td>
<td>-0.008</td>
<td>0.011</td>
</tr>
<tr>
<td>Employed</td>
<td>0.120</td>
<td>0.033</td>
<td>0.060</td>
<td>0.024</td>
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<td>Income</td>
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<td>0.007</td>
<td>-0.131</td>
<td>0.011</td>
</tr>
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<td>Constant</td>
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<td>0.018</td>
<td>-0.478</td>
<td>0.016</td>
</tr>
<tr>
<td>Risk</td>
<td>0.542</td>
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<td>0.519</td>
<td>0.007</td>
</tr>
<tr>
<td>Within-Next Correlation: Purchase</td>
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<td>0.001</td>
<td>0.198</td>
<td>0.002</td>
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<td><strong>Log-Likelihood</strong></td>
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<td>-85075</td>
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<tr>
<td>AIC</td>
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<td></td>
<td>170200</td>
<td></td>
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<tr>
<td>BIC</td>
<td>158130</td>
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<td>170440</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Model Estimates
7 Counterfactuals

To be completed

8 Discussion

In this paper, we develop a model of sequential search that explains consumers’ search and purchase choice, accounting for consumers’ prior information. We estimate this model on a data set of consumers making smartphone search and purchase decisions where we also observe consumers’ prior experiences with smartphones. The model demonstrates that when the prior information is not systematically accounted for in the model, the estimation of consumers’ search cost and preference parameters will be biased.

Our results highlight the role of prior information in consumer search process. For the future work, we plan to run several counterfactual analysis where we vary how much and what information to show to consumers based on their prior history. Our results will provide managers with additional insights when designing the environment in which consumers search to account for both consumers’ prior knowledge and current product information.
References


