Prior Information and Consumer Search: Evidence from Eye-tracking

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Abstract

Do consumers search the brands they know more or less frequently than the brands they are unfamiliar with? In this paper, we attempt to answer this question using data from an experiment with two novel features: (i) survey information on consumers' prior brand ownership, familiarity with each brand, and prior experience using different product features; and (ii) eye-tracking data capturing search behavior at a very granular level. We find consumers are generally more likely to search and buy brands they own and are familiar with, highlighting the importance of accounting for prior information. For this reason, we develop a search model in which both the information obtained during the search process and the information possessed by consumers prior to search are allowed to influence search and purchase decisions. Our model contributes to prior work by modeling search at the brand and attribute level within a Bayesian learning framework. Using this model, we then quantify the impact of prior information on consumer choices, as well as document the estimation bias arising when prior information is absent from the model. Finally, through a series of counterfactuals, we explore the managerial value of prior information data.

Keywords: Consumer Search, Search with Learning, Prior Information, Eye-tracking.

JEL Classification: D83, L81, L86, M31

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1 Introduction

The collection of consumer search data via browsing sessions online or geolocation signals offline has never been more widespread.[1] These new data sets have allowed research on consumer search to flourish (e.g. De los Santos et al. (2012), Koulayev (2014), Chen and Yao (2017), Ursu (2018), Ghose et al. (2019), Gardete and Antill (2020), Yavorsky et al. (2021)). This research has typically focused on modeling consumer decisions *during* the search process, i.e. on modeling the trade-off that consumers make between the cost and the benefit of acquiring brand information.

Our work aims to additionally study the impact that information possessed *prior* to search has on consumer choices. In many retail settings, consumers begin their search with different prior information on the brands available. For example, a consumer who has repeatedly purchased and used an Apple iPad will have a higher stock of prior information about this tablet than about other products available in the market. Such differences in prior information may influence consumer search and purchase decisions. Intuitively, a consumer with more prior information about a brand may need to search less. Alternatively, such a consumer may have a higher valuation for the brand she owned or used before, resulting in a higher propensity to search it over other brands. Ignoring this prior information may lead to incorrect inferences about the motivation for consumer behavior. For example, researchers may mistakenly attribute repeated searches of a brand to low search costs, when instead prior ownership or familiarity with a brand may drive such searches. Also, not accounting for differences in prior information may have managerial implications, since companies frequently use such data to make decisions. For instance, companies vary marketing mix decisions, such as ad targeting, recommendations or pricing, based on previous search and purchase histories, and thus based on consumers' level of prior information. Also, they design loyalty programs based on consumers' past brand usage and ownership. As industries mature and consumers increasingly diverge in their prior brand information, the need to understand and model the role of such prior information will only increase.

In this paper, we develop a model of sequential search with learning that formally accounts for the role of prior information in the search and purchase process. Search is modeled as a Bayesian learning process: consumers are uncertain about a brand's match value, but hold beliefs in the form of priors

[1] Statistics are available at https://hbr.org/2018/06/enhancing-customer-insights-with-public-location-data or https://money.cnn.com/2017/04/05/technology/online-privacy-faq/.

that differ based on consumer prior information about a brand. Through costly search of different brands and their attributes, consumers receive signals about a brand's match value. Consumers use these signals to update their beliefs in a Bayesian manner and decide whether to continue searching or whether to stop and make a purchase decision.

We estimate our model on a novel data set from an experiment completed in 2013 in which consumers made smartphone search and purchase decisions among the top five brands available at the time (Apple, Samsung, Nokia, Motorola, and HTC). Our data have two features that stand out. First, they contain survey results on three different measures of consumer prior information: (i) prior brand ownership, (ii) familiarity with each brand, and (iii) prior experience using different smartphone functions (e.g. camera, calling, texting). This feature of the data allows us to model consumer prior beliefs as fully heterogeneous and to disentangle preference heteorgeneity from state dependence (prior information) in a model of search and choice decisions. Also, these survey data allow us to test how each measure of prior information affects different consumer primitives: prior uncertainty, prior expected valuation and search costs.

Second, in these data we observe consumer search decisions at the very granular level of eye-movements. More precisely, during the experiment, participants' eye movements were tracked revealing which of the five brands and which product attributes (e.g. price, camera, battery) they chose to become informed about every 200-400 milliseconds. This data feature has two consequences for our analysis. First, it allows us to model search at both the brand and the attribute level, contributing to previous empirical work that assumes search occurs solely at the brand level (e.g. Honka and Chintagunta (2016), Chen and Yao (2017), Bronnenberg et al. (2016), Ursu (2018), Ghose et al. (2019), Ursu et al. (2020)).[2] Second, it requires that we properly model search at the eye-fixation level. Unlike in the case where consumers physically visit a store (Yavorsky et al. (2021)) or where they need to click on product links online to obtain information (De los Santos et al. (2012), Chen and Yao (2017), De los Santos and Koulayev (2017), Koulayev (2014), Ursu (2018)), searching by simply moving one's eyes and making another fixation involves different considerations. In particular, given the high frequency with which consumers make search decisions in our setting (the average consumer makes 229 fixations), we expect the computational burden of determining the optimal eye fixation sequence

[2]The exception we are aware of is Gardete and Antill (2020). We describe similarities and differences between our work in the next section. Theory work modeling search at both the brand and the attribute level includes Branco et al. (2012), Branco et al. (2015), Ke et al. (2016).

to outweigh the benefit, leading consumers to use heuristics over optimal search rules. Motivated by this observation, in this paper we use insights from the literature on rational inattention and model consumers as forward-looking agents that use heuristics to make decisions (Gabaix and Laibson (2000), Gabaix et al. (2006), and Hauser (2014)). Such models have been shown to fit data patterns well (Camerer and Johnson (2004), Gabaix et al. (2006), Tehrani and Ching (2020)), including in contexts very similar to our own (Yang et al. (2015)).

These data demonstrate the importance of prior information. In particular, they show that consumers are more likely to search brands they own and are familiar with. Also, consumers are more likely to purchase the brands for which they have more prior information. In other words, prior information helps explain observed search and brand choices. This suggests the need to understand not only how consumers acquire information during the search process, but also how the information possessed by consumers prior to search shapes and influences their choices.

Our granular eye-tracking data also provide new insights into the consumer search process. For instance, we show that consumers most often pick an attribute and search it across multiple brands, rather than investigate multiple attributes of the same brand at once. As a result, consumers frequently return to search a previously inspected option (behavior known as a "search revisit" in the literature, Dang et al. (2020)). These findings strengthen the need for a model with learning where brand-attribute information is revealed gradually through search, since a model without learning (e.g. Weitzman (1979)) assumes all uncertainty about an option is revealed in a single search, eliminating the need for a revisit. Our paper develops exactly such a model.

In estimating the model, we find that prior information plays an important and a diverse role in affecting consumer search behavior. After testing six alternative models of the effect of prior information on consumer primitives, we find that prior ownership increases consumers' evaluation of the product before beginning search. We also show that consumers are less uncertain about brands they are more familiar with before starting to search. Finally, searching product attributes with which the consumer has more prior experience involves paying lower costs.

In addition, we document the estimation bias arising from omitting data on consumer prior information from the model. We find that consumer preferences for brands with high previous ownership or familiarity are overestimated. More precisely, without data on prior information the model interprets searches, that may actually be influenced by preference for a previously owned brand or by lower uncertainty due to familiarity, as motivated by valuable brand information obtained through search. Thus, preferences for such brands are generally inflated. Also, we find that search costs are underestimated when prior information is omitted. The high number of searches we observe occurs in part because consumers like they brands they own and are familiar with, not because they have low search costs. However, without prior information data, the model mistakenly attributes a large number of searches to low search costs.

Finally, we perform a series of counterfactuals to explore the managerial value of consumers' prior information. First, we ask: if consumers had no prior information on the brands available and their attributes, would they purchase the same brands? This counterfactual is meant to quantify the effect of prior information on market shares. We find that removing prior information makes market shares more homogeneous across brands. Also, if consumers had no prior information, then the most familiar brands, Samsung and Apple, would suffer the most (e.g. as much as a 1.4% decrease in market shares when prior ownership is removed), while all other brands would observe an increase in their market shares (e.g. larger than 1% for Nokia when prior ownership is removed). Second, we investigate what companies can do to compensate for a lack of consumer prior information. Of the three measures of prior information we have, familiarity is the only one that companies can influence directly, for example through advertising (for evidence on the effect of advertising on consumer awareness and information, see Ackerberg (2001, 2003), Clark et al. (2009), Terui et al. (2011), Blake et al. (2015), Tsai and Honka (2018), Honka et al. (2017)). Therefore, we wish to explore which brands would benefit from investments in familiarity and whether such investments could compensate for the lack of prior ownership. We find that no amount of familiarity can compensate for the lack of prior ownership for the brands that are most familiar to consumers, Samsung and Apple, but that investments in familiarity could help less familiar brands overcome their lower prior ownership (HTC, Moto, and Nokia). We view these results as adding to our understanding of the managerial value of prior information and helping companies decide when and whether to invest in increasing consumer familiarity given consumers' current level of information. One important managerial takeaway from our counterfactuals is that prior ownership constitutes the best kind of advertising for top brands.

Our approach differs from previous work studying the role of prior information. Two papers are most closely related to our own. First, Jindal and Aribarg (2020) also study the role of prior beliefs in the context of consumer search decisions, but use a lab experiment to elicit consumer prior beliefs about the distribution of market prices for a homogeneous good. In contrast, we jointly estimate how prior information, brand preferences, and search costs affect search and purchase decisions. Our approaches (elicitation versus estimation) are different and complementary. For example, our approach does not require asking consumers to report entire belief distributions to measure their prior information, data that are challenging for companies to obtain outside of a controlled lab experiment. Also, we are able to test how different measures of prior information affect model primitives, to quantify the value of such measures, as well as to perform counterfactuals related to using data on consumer priors to improve marketing strategies. Second, Shin et al. (2012) demonstrate the value of using data on stated preferences (i.e. measures of liking and familiarity) to separate the impact of state dependence from preferences on consumer choices. Our paper uses similar information on consumers' prior choices and familiarity with brands, but we additionally study the importance of state dependence in the context of consumer search decisions, not only choices. For all these reasons, we expect, as well as report, different results than the ones obtained in prior work. For example, we find that in the absence of information on consumer's priors (state dependance), not only brand preferences would be biased, but also search costs would be underestimated, adding to and contrasting with results in both Shin et al. (2012) and Jindal and Aribarg (2020).

The rest of the paper is organized as follows. The next section provides a more detailed overview of our relation and contribution to prior work. Section 3 introduces our data, while in Section 4 we present preliminary reduced-form evidence for the importance of prior information. In Section 5, we present our model, followed by estimation results and counterfactual analysis. The last section concludes and discusses limitations and possible future extensions of our work.

2 Literature review

Closely related to our paper is prior work modeling consumer search with learning. Most models of consumer search, building on the framework of Stigler (1961) or Weitzman (1979), assume that consumers are able to resolve all the relevant uncertainty about a product with just one search. However, these models cannot explain why consumers choose to revisit some products, a pattern that has been established empirically (e.g. Bronnenberg et al. (2016), Dang et al. (2020), Ursu et al. (2020)). To rationalize this as well as other patterns, previous work relaxes the assumption of fully revealed uncertainty through search and allows consumers to gradually learn through search, typically by

Bayesian updating (Branco et al. (2015), Branco et al. (2012), Chick and Frazier (2012), Dukes and Liu (2015), Ma (2019), Ke et al. (2016), Ke and Villas-Boas (2019), Gardete and Antill (2020), Ursu et al. (2020), Lu and Hutchinson (2020)).[3,4] However, this work estimates such search models by assuming homogeneity in prior beliefs (e.g. Ma (2019), Lu and Hutchinson (2020), Ursu et al. (2020)).[5] We also estimate a model of search with Bayesian learning, but we augment data on consumer search and purchase decisions with information on consumers' prior ownership, familiarity, and prior experience with brand attributes. These additional data allow us to model consumers' heterogeneous prior beliefs.

Our results also add to previous survey and experimental work that shows the importance of consumer prior information in the context of search (Moore and Lehmann (1980), Bettman and Park (1980), Punj and Staelin (1983), Johnson and Russo (1984), Brucks (1985), Srinivasan and Agrawal (1988), Srinivasan and Ratchford (1991), Moorthy et al. (1997), Jindal and Aribarg (2020)), as well as recent theoretical work on prior ownership and search (Ning and Villas-Boas (2020)). Some work finds that prior information encourages more search, since it increases the ability of the consumer to process new information (Johnson and Russo (1984)). Other work finds that consumers with a higher inventory of prior information have a reduced need for external search (Moore and Lehmann (1980), Bettman and Park (1980)). Finally, other work shows there may be a U-shaped or context dependent relation between prior information and search (Bettman and Park (1980), Johnson and Russo (1984), Punj and Staelin (1983), Brucks (1985), Srinivasan and Agrawal (1988), Srinivasan and Ratchford (1991)). We also investigate the relation between prior information and search and find that consumers are more likely to search products they own and are familiar with. We contribute to this work by developing and estimating a model that formalizes the joint effect of prior information, preferences, and search costs on consumer choices.

Within the literature on the relation between prior information and search, the most closely related paper to our own is that of Jindal and Aribarg (2020). In their paper, the authors set up a lab experiment in which consumer beliefs about the market distribution of prices for a homogeneous good are elicited before and after each search. The authors then investigate the estimation bias that arises when data

[3]Our model's focus is on learning brand match values. Previous work has also studied cases where consumers learn about the market distribution of rewards (Koulayev (2013),De los Santos and Koulayev (2017), Hu et al. (2019)).

[4]In parallel, when studying consumers' repeated purchase decisions, researchers also allow consumers to learn from prior purchases and update their beliefs in a Bayesian manner across purchase incidences (e.g., Erdem and Keane (1996), Ackerberg (2001), Ching et al. (2013) and Iyengar et al. (2007)). However, we note that such models study repeated brand choices, rather than consumer search decisions.

[5]A model of prior beliefs in a non-sequential search environment can be found in Jerath and Ren (2021).

on prior beliefs are not available and researchers assume instead rational expectations. Our paper differs in a number of important ways. First, we jointly estimate how prior information, brand preferences, and search costs affect consumer choice. This approach differs from and complements the elicitation approach used by Jindal and Aribarg (2020), since it does not require asking consumers to report entire price distributions to measure their prior information. Instead, we use data that are more commonly available to companies, such as data on consumers' prior ownership of a brand (available through purchase histories) and brand familiarity (available through consumer surveys or from search/browsing histories). These data also allow us to test how different measures of prior information affect model primitives, to quantify the value of such measures, as well as to perform counterfactuals related to using data on consumer priors to improve marketing strategies. Also we focus on the market for a heterogeneous good, where consumers search brand-attribute combinations to learn their match value with a brand, rather than a homogeneous good where consumers search for prices. For all these reasons, we expect, as well as report, different results. In Jindal and Aribarg (2020), consumers are pessimistic about their ability to find low prices. This bounds search costs from above (to allow search even when consumers expect high prices), leading to an overestimation of search costs if researchers wrongly assume consumers have rational expectations. In our data, we find higher search costs when accounting for prior information because consumers like searching the brands they have more information about. Thus, they search more not because of low search costs, but rather because of their prior preference for certain brands. We believe both results contribute to our understanding of the relation between prior beliefs and search costs.

Our work also relates to the literature on disentangling state dependence and heterogeneity from consumer choices (e.g. Dubé et al. (2010), Shin et al. (2012)). Most closely related is the work of Shin et al. (2012), which uses data on brand liking and familiarity to separate the impact of state dependence from preferences on consumer choices. We use similar data on prior information to capture state dependence, but we additionally study the importance of state dependence in the context of search decisions. Here we show that in the absence of prior information data (reflecting state dependence) not only brand preferences would be upward biased (as shown in Shin et al. (2012)), but also search costs would be underestimated.

One contribution of our paper is the development of a search model at the brand-attribute level. Most prior empirical work assumes search occurs only at the brand level (Honka and Chintagunta

(2016), Chen and Yao (2017), Bronnenberg et al. (2016), Ursu (2018), Ghose et al. (2019), Ursu et al. (2020)). The only exception we are aware of is Gardete and Antill (2020). In that paper, the authors observe when consumers choose to click to reveal more attributes of the same product. Search fully reveals consumers' uncertainty about an attributes, so full information about a product can be reached in finite time, since each product has a finite set of attributes. Therefore, consumers have no reason to revisit the same brand-attribute combination and there is a finite number of revisits possible at the brand level. We also model search at both the brand and the attribute level. However, we use a model of search with learning to do so. In our model, information revealed through search helps consumers update their beliefs, but their uncertainty about a brand is never fully resolved (except in the limit). This model allows us to rationalize the pattern we observe in Section 4 that consumers search a brand's same attribute more than once (search revisit), behavior which would not be consistent with a model without learning at the brand and attribute level. Also, since our data are at the eye-fixation level, rather than at the click level, the search decisions we observe are a lot more granular.

Our paper also relates to work on rational inattention, which proposes that consumers use heuristics to make choices (e.g., Gabaix and Laibson (2000), Gabaix et al. (2006) and Hauser (2014)). Such models have been shown to fit data patterns well (Camerer and Johnson (2004), Gabaix et al. (2006), Tehrani and Ching (2020)), including in contexts very similar to our own (Yang et al. (2015)). We provide a new application of heuristics to models of search with learning and heterogeneous prior beliefs.

Lastly, our paper is related to prior work measuring eye-movements to inform models of consumer decision-making. Eye-fixations have been shown to be indicators of consumer attention (Wedel and Pieters (2000)), utilities (Meißner et al. (2016)), searches (Shi et al. (2013), Yang et al. (2015), Lu and Hutchinson (2020)), and choices (Martinovici et al. (2021)). Relatedly, Hu et al. (2013) show that data on eye-movements and fixation duration can proxy for consumer beliefs about which option is to be preferred for a next draw in repeated Bandit experiments that allow consumers to update their beliefs within a learning framework. Building on this work, we will use eye-tracking data to study search and belief updating rules. Also, previous work has found that heuristics in decision-making can lead to distinct eye-movement patterns (Orquin and Loose (2013)) and it has been proposed to use Bayesian methods to build models that closely examine such eye-movements (e.g. Wedel and Pieters (2008)). Our paper develops such a model.

3 Data

3.1 Data Description

Our data were collected in the period June 17th to 26th in 2013 by Tobii Insight[6] as part of a litigation case. Data collection resulted from an experiment designed by Tülin Erdem and Rik Pieters in collaboration with Analysis Group. The experiment mimicked a common online shopping experience for smartphones. Specifically, participants were asked to evaluate five smartphones and chose one to purchase. The participants in this experiment were recruited from three US cities (San Diego, Cincinnati, and Washington DC) using Tobii's partner organizations' database, which ensures the representativeness of the participant pool. The participants were at least 18 years old and were required to not have any eye problems, such as nystagmus. Also, the recruited participants could not have worked for a research company, advertising agency or technology company. Participants were required to own a cell phone at the time of their participation in the experiment and to intend to purchase a smartphone within 9 months. There were four major segments of participants in the population: 1) Apple owners; 2) Samsung owners; 3) other brand owners; 4) non-smartphone consumers. To ensure the representation of participants in our experiment, we applied a stratified sampling method to draw equal numbers of participants from each of these four segments. The recruited participants were scheduled to visit the research facilities solely to complete our experiment and they were offered $50 to cover the transportation costs and their time.

There were in total five smartphones under comparison: Samsung Galaxy Note II, Apple iPhone 5, HTC One, Motorola Droid RAZR MAXX HD, and Nokia Lumia 920. For the rest of this paper, we will refer to these smartphones solely by their brand names. Prices were as follows: $249.99 for Apple and Samsung, $199.99 for HTC and Motorola, and $99.99 for Nokia. The determination of the smartphones used in the experiment was guided by the top 20 Google search results for various keywords such as 'best top smartphone 2013', and by mentions in consumer reports. We note that participants did not own any of the five products used in the experiment, i.e. an Apple product owner did not own the iPhone 5, but might have owned an iPhone 3 for example.

The brand attributes displayed to participants were chosen to be consistent with the attributes shown on (i) the four major carrier websites (AT&T, Verizon, Sprint and T-Mobile); (ii) the top four

[6] https://www.tobiipro.com/insight/.

electronic retailers (Amazon, Bestbuy, Target mobile and Walmart); and (iii) the top independent review websites (Verge, CNET, PCWorld and gdgt.com). In Figure 1, from top to bottom, we display the attributes that consumers saw. These were categorized into seven groups as 'Brand' (including a photo of the product and color option), 'Price', 'Technical' (including 'Wireless Capabilities' and 'Operating System'), 'Size' (including 'Display'), 'Battery', 'Camera', and 'Memory'. Participants were randomly assigned to one of three complexity conditions.[7] All three complexity conditions had these seven parent attribute categories, but the number of attributes that nested within these categories varied from condition to condition. For example, while there was only one attribute under 'Camera' in the low complexity condition, there were three attributes under 'Camera' in the high complexity condition. Overall, the low complexity condition contained 18 attributes, the medium complexity condition contained 29 attributes, and the high complexity condition contained 39 attributes. Figure 1 displays the options that participants saw in the low complexity condition, while Figures A-1 and A-2 in Appendix 9.1 illustrate the options available to participants in the medium and high complexity conditions, respectively. The information displayed to participants about each of these attributes was the same in each condition (for example, Apple was shown with a price of $249.99 in all conditions). Under each of the three complexity conditions, there were five unique combinations of attribute and brand orders, for a total of 15 unique stimuli. The order of the brands (columns) and attributes (rows) displayed on the screen was randomized to control for the effect of position on consumer search decisions and final choices.[8]

During the experiment, participants' eye movements were tracked revealing which of the five brands and which product attributes (e.g. price, camera, battery) they chose to become informed about. Eye movements were recorded using Tobii 60XL infra-red eye-trackers built into the 24-inch computer screens participants interacted with. This eye tracker offers unobtrusive tracking of both eyes, increasing the quality of our measurements. The eye-movement data of these participants was described by their attention to different areas of interest (AOI) on the screen, such as the seven main attribute categories for each of the five brands.[9] An eye fixation in the data is defined as a period of 200-400 milliseconds during which the eye is relatively fixed on an area.[10]

[7] Previous work suggests that varying the number of product attributes available to consumers may increase choice complexity (Malhotra (1982)), which in turn can affect how consumers acquire and process information (Swait and Adamowicz (2001), Payne (1976)).

[8] Only brand and price were always shown at the top - the order of all other attributes was randomized in each condition.

[9] For an illustration of eye-fixations in our experiment, see Figure A-3 in Appendix 9.1.

[10] These data were generated using standard settings in the Tobii eye-tracking software.

Consumers were asked to pick only one brand to purchase and they could take as much time as they needed to make that decision. There was a 'Click to buy' button next to each of the options. Once a consumer clicked on that button, she was asked to confirm her choice, ending the experiment.

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Insert Figure 1 about here

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In addition to choosing among smartphones, consumers were asked to fill out a survey. We used consumers' answers to this survey to construct three measures of prior information: prior ownership, familiarity, and prior experiences. The exact questions asked to construct each measure were:

- **Prior ownership**
  - Do you currently own a smartphone? (0 or 1; 1 means own a smartphone).
  - What is the current model or brand of the smartphone you own? (choice among the five brands in the experiment, or 'None' for consumers who do not have smartphones and 'Others' for consumers who owned brands that are not included in the experiment).
- **Familiarity**
  - How familiar are you with the brands in the experiment? (measured on a scale from 1 to 7 where 1 corresponds to 'Not at All' and 7 corresponds to 'Extremely Well').
- **Prior experience**
  - How much do you use each of the functions of the smartphone: video taking, photo taking, internet browsing, video chatting, texting, calling, etc.? There were seven options participants could choose from: 'Never', 'Less Often than Once per Month', 'Less Often than Once per Week', 'At Least Once Per Month', 'At Least Once Per Week', 'Nearly Every Day', 'Several Times Per Day'. We converted responses to a scale ranging from 0 to 1, with equal weight to each option, where 0 corresponds to 'Never' and 1'corresponds to 'Several Times Per Day'. We used this question to measure consumers' prior experience with five of the seven attributes ('Technical', 'Size', 'Battery', 'Camera', and 'Memory'). For the other two attributes ('Brand' and 'Price'), we obtained information on consumers' prior experience from a different survey question which asked "How knowledgeable or not

knowledgeable do you consider yourself about smartphones?". Answers were reported on a rating scale from 1 to 7.

There were in total 460 consumers who participated in the experiment. We observe a complete set of eye-movements (e.g. participants whose eye-trackability was not less than 60% or who did not present any technical complications during eye tracking), as well as complete survey responses and brand choices in the experiment for 342 of them, who will be the focus of our study.

3.2 Summary Statistics

Our final data sample consists of 342 consumers and 78,617 observations (78,275 eye-fixations, and 342 individual consumer brand choices). Each consumer makes on average (median) 229 (186) fixations on the products and their attributes displayed on the screen. Approximately 79% of the consumers in our data own a smartphone.

Table 1 reports the distribution of two measures of prior information (prior ownership and familiarity with each of the five brands). It can be seen that consumers are most likely to own an Apple smartphone before the experiment, and to be familiar with either Samsung or Apple smartphones. Sizable fractions of consumers also own HTC, Motorola and Nokia smartphones, with the latter being the least popular. Approximately 7% of consumers own other brands than the ones available in the experiment. The correlation between prior ownership and familiarity is relatively small, ranging from 0.12 to 0.41 depending on the brand, showing a large variation across consumers in these two measures. This is also evidenced by the large standard deviations in familiarity across consumers for each brand (approximately 2 on 7 point scale).

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In Table 2, we summarize our third measure of prior information given by consumers' prior experiences with various smartphone functions, such as voice-calling or photo-taking. Note that this measure does not vary across brands. In total, there were 16 functions consumers were asked about in the survey, which we later grouped to coincide with five of the relevant categories of attributes: Camera (e.g. photo-taking and video-taking), Battery (e.g. voice-calling, texting, and video-chatting), Size (e.g. dimensions, weight), Technical (e.g. OS, Wifi, warranty) and Memory (e.g. RAM). We find that consumers are most experienced with the 'Battery' attribute, since it relates to the essential communication functions of the phone. In contrast, consumers are least experienced with the 'Technical' and the 'Camera' attributes. In 2013 when we collected our data, photo-taking and video-taking with a smartphone were still new functions to most users, [11] which explains consumers' low level of experience with these attributes. Across consumers we also find that there is a large variation in their experience with each attribute. Similarly, consumers varied in their knowledge of the other two attributes they could gaze at during the experiment: 'Brand' and 'Price'. Their measure of prior experience with these attributes had an average (standard deviation) equal to 4.67 (1.59).

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Insert Table 2 about here

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Finally, to summarize consumer choices, we look at the brand choice share at the end of the experiment. We find that most consumers choose Samsung (29.24%) and Apple (25.73%), followed by HTC (21.35%), Motorola (16.08%), and Nokia with the smallest share of choices (7.60%)

4 Reduced-Form Evidence

In our data we observe consumer eye fixations on the screen on various AOIs. We interpret these fixations as decisions to search specific brands and their attributes, consistent with previous work (e.g. Shi et al. (2013), Yang et al. (2015), Lu and Hutchinson (2020)). In addition, we observe which brands consumers clicked to buy at the end of the experiment, actions which we interpret as their final brand choices. Finally, the survey consumers filled out gives us insights into consumers' prior information on the available brands and their attributes. In this section, we present reduced-form evidence describing consumer search decisions and brand choices, as well as relate consumers' prior information to these decisions.

4.1 Relation between Prior information, Search Decisions, and Brand Choices

We start by asking whether consumers search the brands they know more or less frequently than the brands they are unfamiliar with. To control for the fact that some consumers search longer than others, we construct our dependent variable as the percentage of a consumer's total searches that are

[11] For more information, please refer to www.nytimes.com/2014/02/06/technology/personaltech.

attributed to a given brand. We then regress this measure on brand intercepts and prior information. In Table 3 we show that consumers in our data prefer to search Samsung most frequently, closely followed by Apple and HTC. To study the importance of prior information data, in the second column of Table 3 we add an indicator for the brand that the consumer owned previously, as well as include the consumer's familiarity level with each brand in the regression. Prior experience does not vary at the brand level (only across attributes) for a given consumer, so it cannot affect brand-level decisions, and is therefore omitted from this analysis.[12] We find that both prior ownership and familiarity have a positive effect on the decision of the consumer to search a brand. In other words, consumers are more likely to search brands they owned prior to the experiment and brands they are more familiar with. In addition, when controlling for prior information, we see that brand intercepts become smaller or insignificant. This suggests that consumers' prior information captures part of the value that would otherwise be attributed to consumer preferences for a brand.

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Insert Table 3 about here

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We also show the effect of prior information on searches in Figure 2. Here we see that brands that were previously owned accounted for approximately 27% of a consumer's searches, while other brands account for only 17% of searches (on average). Also, we find that the effect of familiarity on searches is monotonically increasing: the more familiar a brand is, the higher its percent of searches. For example, moving from the lowest familiarity level (1) to the highest (7) increases the percent of searches of a brand from about 17% to more than 25%

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Insert Figure 2 about here

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Second, we consider consumers' final brand choices. Towards this end, we run a conditional logit model at the consumer level with their brand choice as the dependent variable, and brand intercepts (Nokia serves as the reference brand), prior ownership and familiarity with a brand as explanatory variables. In addition, in one specification, we control for the percent of brand searches. Once again,

[12]Similarly, the complexity level of the condition a participant was assigned to does not vary across brands and is therefore omitted from the analysis.

prior experience does not vary across brands, so is omitted from this analysis.[13] Our results are presented columns (3), (4) and (5) in Table 3. Not surprisingly, most consumers end up choosing either Samsung and Apple, with a slight advantage for Samsung. More interestingly, we show again that prior ownership and familiarity both have positive and significant coefficients. This result suggests that consumers are not only more likely to search the brands they own and are more familiar with, but are also more likely to choose these brands. After accounting for prior information and brand searches (columns 4 and 5), brand intercepts become largely insignificant. Thus, we find once more that the amount of attention given to each brand, summarized by consumers' prior information of the brand and the percent of brand searches, capture consumers' brand value. Finally, our measures of model fit suggest the importance of accounting for prior information when studying consumer choices.

We also illustrate the effect of prior information on consumer choices in Figure 3. Brands that were previously owned have a high likelihood of being purchased (more than 50%). Familiarity also has a monotonically increasing effect on brand choices that is even larger in magnitude than the effect on search decisions: moving from the lowest familiarity level (1) to the highest (7) increases choice probabilities from about 10% to more than 40%.

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Insert Figure 3 about here

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4.2 Evidence of Consumer Learning

Consumers can choose to search across brands (e.g. search Apple versus Samsung), or within brands, choosing which attributes to become informed about (e.g. price vs. memory). To illustrate this decision, in Figure 4, we plot the percentage of fixations performed on different brand-attribute combinations, averaged across consumers. We find that for the majority of all fixations (more than 40% of the average consumer's fixations), consumers repeatedly look at the same brand-attribute combination as on the previous fixation. This suggests that their uncertainty about that brand-attribute combination was not resolved over the course of one or a few fixations. Rather, consumers repeatedly search a brand's same attribute (search revisit), behavior consistent with consumer learning.

[13]Similarly, the complexity level of the condition a participants was assigned to does not vary across brands and is therefore omitted from the analysis.

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Insert Figure 4 about here

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When consumers do not repeat a fixation, we find that they most frequently search horizontally (i.e. consider the same attribute as on the previous search, but of a different brand), rather than vertically (i.e. looking at multiple attributes of the same brand) or rather than jumping across brand-attribute combinations to change both the brand and the attribute. As a result, consumers frequently return to search a previously inspected option, i.e. they perform a search revisit. We also confirm that search revisits are frequent in our data. In Figure 5, we plot the percentage of fixations that are revisits at both the brand level and the brand-attribute level. In both cases, we find that consumers repeatedly return to revisit an option, with a stronger effect at the brand level (as expected). For example, we show that more than 85% of consumers revisit all five brands, and the majority of the remaining consumers (8%) revisit four of the five brands. To rationalize these patterns, in the next section we will introduce a model of search with learning, where consumers gradually reveal information about a brand through search. Models without gradually revealed information through search cannot explain why consumers return to search the same option (brand-attribute combination) again, since such models assume all uncertainty about an option is revealed in a single search. We also show the need to model search with learning in our case by documenting the misleading results that are produced by fitting a model of search without learning on our data (see our results of the Weitzman (1979) model in Table B-1 in Appendix 10.1).

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Insert Figure 5 about here

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The results we presented in this section highlight the importance of prior information in explaining observed search and brand choices. Thus, they suggest the need to understand not only how consumers acquire information during the search process, but also how the information possessed by consumers prior to search shapes and influences their choices. In addition, our results reveal the importance of modeling search with learning at the brand-attribute level, to fully capture all search decisions (i.e. including revisits) consumers are observed to make. The next section introduces a model that reflects and incorporates these results.

5 Model

5.1 Consumer problem

Consider a consumer $i \in \{1, \ldots, N\}$ who seeks to purchase a brand $j \in J$. The consumer faces uncertainty about her match value with each brand j, but can (partially) resolve this uncertainty by searching j. This search decision involves paying a search cost, but reveals information to the consumer that may aid her choice. We build on Ursu et al. (2020) and model consumer search as a learning process:[14] a consumer holds beliefs about a brand's match value in the form of priors; by searching, the consumer pays a cost and receives a signal of the brand's match value; she uses this signal to update her beliefs in a Bayesian manner; after every search, the consumer decides whether to continue searching, or whether to stop, in which case she chooses which brand to purchase. We propose that such search decisions occur sequentially, given the sequential nature of eye-fixations.

We extend this model in two directions. First, we allow search to occur not only at the brand level, but also at the brand-attribute level. In other words, if the consumer decides to continue searching, she chooses a brand j and an attribute $l \in L$ to search. Second, in our data, we observe three measures of consumer' prior information (prior ownership, familiarity, and prior experience), which allow us to model consumer prior beliefs as fully heterogeneous. In our empirical specification below (Section 5.3), we describe how we parameterize the model as a function of this prior information.

The consumer is uncertain about her true match value for a brand, which is normally distributed with unknown mean μ_{ij} and known variance. She holds beliefs about her match value for brand j, which at time $t = 0$ are given by

$$N(\mu_{ij0}, \delta_{ij0}^2). \tag{1}$$

To obtain product information, the consumer needs to pay a search cost, c_{il}. Because consumers can search different attributes, we let the search cost vary across brand attributes.[15]

By searching product j at time t, the consumer obtains noisy but unbiased signals s_{ijt} from the true distribution of match values given by

$$s_{ijt} \sim N(\mu_{ij}, \sigma_i^2). \tag{2}$$

[14] In Ursu et al. (2020), consumers obtain signals after every minute spent searching; in our paper, one signal is obtained after every eye-fixation.

[15] Our robustness checks in Table B-2 (Appendix 10.2) also test for the possibility that search costs do not vary across attributes, but find that our current specification has a better fit.

After observing a signal s_{ijt} at time t, the consumer uses Bayes' rule to construct her posterior belief about brand j, given by $N(\mu_{ijt+1}, \delta^2_{ijt+1})$, where

$$\mu_{ijt+1} = \frac{\frac{\mu_{ijt}}{\delta^2_{ijt}} + \frac{s_{ijt}}{\sigma^2_i}}{\frac{1}{\delta^2_{ijt}} + \frac{1}{\sigma^2_i}}, \tag{3}$$

$$\delta^2_{ijt+1} = \frac{1}{\frac{1}{\delta^2_{ijt}} + \frac{1}{\sigma^2_i}}. \tag{4}$$

Because draws are independent, the consumer does not learn about the match value of one brand by searching another. Therefore, after observing signal s_{ijt}, only the posterior belief of j changes.

To understand why in our model the consumer searches brand-attribute combinations, rather than only brands, we recall that even though signals are brand-specific, search costs vary across attributes. Thus, when deciding what to search, the consumer weighs in both brand and attribute considerations.[16]

At a moment t, the consumer holds beliefs about her match with a brand j that are characterized by μ_{ijt} and δ^2_{ijt}. These beliefs affect the utility from stopping her search and buying j at t. More formally, we model consumer i's utility from choosing brand j at time t as

$$u_{ijt} = v(\mu_{ijt}, \delta_{ijt}) + \epsilon_{ijt}, \tag{5}$$

where utility is a function of prior beliefs and an idiosyncratic shock ϵ_{ijt} that is unobserved by the researcher, but known to the consumer before search (Ursu et al. (2020)).

5.2 Search and Choice Rules

Every time period t, the consumer decides whether to continue searching, in which case she chooses a brand j and an attribute l to search, or whether to stop, in which case she chooses which brand to purchase. In this section, we describe consumer decisions that are relevant for our setting where searching involves simply moving one's eyes and making another fixation on the screen. This setting differs from most other settings considered in the search literature, where consumers physically visit a

[16] In an extension of our model, we also allow the signal variance to vary across attributes (specified as σ^2_{il}). In this case, consumers observe brand-attribute signals, which they combine into a belief about their brand match values after every search. Although this model can be accommodated theoretically within our setup, the data suggest that the model presented in this section has a better overall fit (for details, see Table B-2 in Appendix 10.2).

store (Yavorsky et al. (2021)) or where they need to click on product links online to obtain information (Chen and Yao (2017), De los Santos et al. (2012), De los Santos and Koulayev (2017), Koulayev (2014), Ursu (2018)). More precisely, consumers in our setting make a large number of search decisions (229 on average). Therefore, we expect the computational burden of determining the optimal decision for each of the eye fixations consumers make to outweigh the benefit, leading consumers to prefer heuristics.

Motivated by these considerations, we rely on the literature on rational inattention and model consumers as forward-looking agents that use heuristics to make decisions. Such heuristics have been shown to perform well in explaining consumer behavior (Camerer and Johnson (2004), Gabaix et al. (2006), Tehrani and Ching (2020)). We follow Gabaix et al. (2006) and Yang et al. (2015) and model consumers *searching as if they have to make a purchase decision right after the immediate search* (i.e. as if the next search decision is their last). That is, consumers use a one-step ahead decision rule.[17] If instead consumers used an $n > 1$ step ahead decision rule, our estimates would serve as lower bounds for the consumer utility and search cost parameters obtained using such a decision rule.

At every point in time, the set of available actions to the consumer is given by $A = \{Search, Choice\}$, which is constant across consumers and time. With slight abuse of notation, let an action $a \in Choice = \{1, \ldots, J\}$ denote a brand, while an action $a \in Search = \{1, \ldots, J \times L\}$ denote a brand-attribute combination.

At t, the consumer faces a trade-off:

- Stop searching and **choose**

$$\max_{j \in Choice} v(\mu_{ijt}, \delta_{ijt}) + \epsilon_{ijt}. \tag{6}$$

- **Search** product j and attribute l and expect to receive the maximum utility derived from choosing one of the alternatives immediately thereafter

$$\max_{(j,l) \in Search} -c_{il} + \max_{j,j' \in Choice} \{v(\mu_{ijt}, \delta_{ijt+1}) + \epsilon_{ijt}, v(\mu_{ij't}, \delta_{ij't}) + \epsilon_{ij't}\} + \eta_{ijt}. \tag{7}$$

In words, if the consumer decides to stop searching, then she chooses the brand with the highest revealed utility at time t, according to equation (6). If instead the consumer decides to continue searching, then she will determine which (j,l) combination to search. As shown in equation (7), the

[17] The decision rule we use lies in between a myopic rule (consumers' payoff does not depend on future decisions) and an optimal fully forward-looking rule (consumers' payoff depends on all possible future decisions). For computational reasons, we cannot extend the model to a fully forward-looking framework. Given the high frequency with which consumers search (eye movements) in our context, we also expect consumers to prefer heuristics. Also, a myopic rule will not fit our data. Finally, as mentioned above, heuristics based on the one-step ahead model have been shown to perform well in practice (Camerer and Johnson (2004), Gabaix et al. (2006), Tehrani and Ching (2020)), and work in marketing and economics has successfully applied such models in a search context (see Hodgson and Lewis (2020), Ursu et al. (2022)). For more details on why we use a one-step ahead decision rule, see Appendix 16.

value of searching (j,l) is given by the cost of searching, c_{il}, and the benefit of searching once more, reducing uncertainty to increase the purchase utility, and then stopping immediately thereafter to make a purchase decision. After searching (j,l), the consumer may expect to purchase j or any of the other brands $j' \neq j$ that were not just searched. The options that are not considered for search at t have an expected utility of $v(\mu_{ij't}, \delta_{ij't})$, i.e. a utility unchanged due to a lack of search. In contrast, for the brand j that is considered for a search the expected utility is given by $v(\mu_{ijt}, \delta_{ijt+1})$. Since the value of the posterior variance evolves deterministically, we assume the consumer can compute the value of δ^2_{ijt+1} for the brand j considered for search. Finally, we model the search decision as containing an additional idiosyncratic shock, η_{ijt}, that is unobserved to researchers, but observed by the consumer (similar to how purchase utilities contain information that is unobserved to researchers). This idiosyncratic shock allows us to express search and choice probabilities in closed form (see the next section).

To link our model to prior work (Weitzman (1979), Honka and Chintagunta (2016), Chen and Yao (2017), Ursu (2018), Ursu et al. (2020)), we note that equation (6) corresponds to the *choice rule* (which option to choose once search ceases), equation (7) corresponds to the *selection rule* (which option to search if continue searching), while the choice between equation (6) and (7) defines the *stopping rule* (whether to stop or continue searching).

5.3 Empirical Specification

In this section, we describe the empirical version of our model that we will take to data. Towards this end, we first discuss how we use our three measures of prior information to model consumer behavior.[18] It is not clear *a priori* how each measure of prior information affects model primitives and thus consumer choices. Indeed, previous work finds mixed evidence. For example, it has been shown that a higher inventory of prior information discourages search, consistent with an effect on prior uncertainty (Moore and Lehmann (1980), Bettman and Park (1980)), and that prior information affects information processing abilities, consistent with an affect on the signal variance (Johnson and Russo (1984)), and even more complicated U-shaped and context dependent relations (Bettman and Park (1980), Johnson and Russo (1984), Punj and Staelin (1983), Brucks (1985), Srinivasan and Agrawal (1988), Srinivasan and Ratchford (1991)).

[18] To disentangle individual heterogeneity and state dependence, we follow Shin et al. (2012) and use our survey data on prior information from previous choice settings to capture state dependence (affecting consumer prior beliefs in our model), while choices consumers make in the current study reveal heterogeneity in preferences.

Although we cannot directly test the relation between prior information and beliefs since the latter is unobserved, we proceed in two steps. First, we use prior work (Shin et al. (2012)) and our understanding of the behaviors captured by our prior information data to propose one specification of the role of prior information. More precisely, prior brand ownership is a direct result of consumer prior choices among brands. Therefore, it reflects consumer preferences and it is natural to expect that prior ownership should affect the consumers' prior mean valuation. Brand familiarity reflects the consumer's awareness and level of information about a brand. This can be obtained from prior searches, purchases or other interactions with a brand, such as advertising. Therefore, we expect the consumer's familiarity with a brand to affect her prior uncertainty level. Since the consumer's utility is a function of both her prior mean and her uncertainty level (see equation (5)), then both prior ownership and familiarity will affect consumer brand choices, matching our reduced form results (Section 4). Our reasoning is consistent with that found in prior work. In Shin et al. (2012), it is assumed that "familiarity" affects prior uncertainty, while "liking" affects the prior mean beliefs (similar to the effect of prior ownership in our case, since this captures previous purchase decisions, and therefore consumer preferences). Finally, attribute prior experience does not vary across brands for a given consumer. Therefore, it cannot explain brand choices directly. Rather, we expect that it does not directly affect utility, but only search costs.

Second, we estimate our model under almost all possible combinations (six alternatives) of effects of prior information on model primitives (see Table B-2 in Appendix 10.2). For example, we check whether a model where both prior ownership and familiarity affect the prior mean, or where the roles of prior ownership and familiarity are flipped better fit the data. Also, we check whether a model where experience does not affect search costs, but affects the signal variance fits the data better.[19] We find that all alternative specifications fit our data worse than the model we present in this section. Finally, we also check in Table B-1 of Appendix 10.1 whether a model without learning leads to a better fit, and again find that our proposed model is superior.

Given these considerations, we propose the following empirical specification of our model. Let a consumer i search among five brands $j \in J$: {Samsung, Apple, HTC, Motorola, Nokia}. Each brand has a set of seven attributes, given by $l \in L$: {Brand, Price, Technology, Size, Camera, Memory, Battery}. The consumer is uncertain about her match value with a brand, but holds beliefs about it, which she

[19]Since experience does not vary at the brand level, it cannot affect the prior mean or variance.

updates through search. We let the prior mean of these beliefs be a function of prior ownership, as per

$$\mu_{ij0} = \lambda_i + \beta_i PriorOwnership_{ij}, \tag{8}$$

where $PriorOwnership_{ij}$ is a binary variable equal to 1 for the brand the consumer previously owned and to 0 for brands she did not own. The variable λ_i denotes the value of the prior mean for consumers who do not own a smartphone device at the time of the experiment. Both effects may be heterogeneous across consumers. In our estimation, λ_i is constant across consumers, to ensure identification (see Section 5.5 for more details).

We model the prior variance as a function of familiarity, as per

$$\delta^2_{ij0} = \frac{1}{exp(\gamma_i Familiarity_{ij})}. \tag{9}$$

We model this relation in exponential form to ensure that variance is non-negative. Once again, we allow familiarity to have a heterogeneous effect.

Through search, the consumer obtains noisy but unbiased signals from the true distribution of match values, which we specify as $N(\mu_{ij}, \sigma^2_i)$. The mean of the signal for each brand is a function of brand intercepts that may be heterogeneous across consumers. Note that in our data, prices and other smartphone attributes do not vary within a brand. Therefore, with brand intercepts in the model, we cannot separately estimate consumer price sensitivity or directly include the level of other smartphone attributes in the model. We let the signal variance be given by $\sigma^2_i = \theta^2_i$. As in other models of learning based on Bayes' rule, only the ratio of prior variance to the signal variance can be identified. Therefore, we cannot include a constant in the prior variance specification, since it would not be separately identified from θ_i in the signal variance.

We use data on our third measure of prior information (prior experience) to model the search cost as follows

$$c_{il} = exp(\kappa_i + \omega_i PriorExperience_{il}), \tag{10}$$

where κ_i denotes the mean search cost and ω_i determines departures from the mean search cost due to differences in prior experience across consumers and attributes. To ensure that search costs are positive, they are modeled as exponential functions, consistent with prior work (e.g., Chen and Yao (2017), Ursu (2018)). The complexity condition to which the consumer was assigned does not vary across brands, so its potential effect on search decisions will be captured by the mean search cost. Search costs do not account for a brand's position on the screen, since brands were displayed horizontally and were randomly ordered on the screen, minimizing the effect of order on search (Ursu (2018)).

We model consumer i's utility from choosing brand j at time t as

$$\begin{aligned} u_{ijt} &= v(\mu_{ijt}, \delta_{ijt}) + \epsilon_{ijt} && (11)\\ &= -exp\left(-r\mu_{ijt} + \frac{r^2}{2}\delta^2_{ijt}\right) + \epsilon_{ijt}, && (12) \end{aligned}$$

where the consumer utility function has the constant absolute risk-aversion form with risk coefficient r, capturing diminishing returns from additional increases in utility (following Ching and Ishihara (2010), Tehrani and Ching (2020)). Utility is a function of the consumer's beliefs, i.e. an increasing function of the posterior mean and a decreasing function of her remaining uncertainty. Both these measures are functions of consumers' prior mean and uncertainty, and thus functions of prior ownership and familiarity. In addition, the consumers' utility is affected by an idiosyncratic shock ϵ_{ij} that is unobserved by the researcher, but known to the consumer before search. Consistent with prior work, we assume this shock is distributed using the type I extreme value (T1EV) distribution (Toubia et al. (2012), Tehrani and Ching (2020)).

5.4 Likelihood Function

Recall that at every point in time, the set of available actions to the consumer is given by $A = \{Search, Choice\}$, with an action $a \in Choice = \{1, \ldots, J\}$ denoting a brand, while an action $a \in Search = \{1, \ldots, J \times L\}$ denoting a brand-attribute combination. In our study there are five brands and seven attributes, so the consumer can choose among 35 different possible brand-attribute combinations to search and five brands to purchase, resulting in a set A with 40 options available at every t. If both types of idiosyncratic shocks, ϵ_{ijt} and η_{ijt}, are distributed using the type I extreme value distribution, then the probability of a consumer i taking action $a \in A$ at time t is given by

$$P_{iat} = Prob(i \text{ takes action } a \text{ at } t) = \frac{exp(EV_{iat})}{\sum\limits_{a' \in A} exp(EV_{ia't})}, \tag{13}$$

where

$$EV_{iat} = \begin{cases} v(\mu_{iat}, \delta_{iat}) & \text{if } a \in Choice \\ -c_{il} + log\left[\sum_{j=1}^{J} exp(v(\mu_{ijt}, \delta_{ijt}))\right] & \text{if } a \in Search \ \& \ a = (j, l). \end{cases} \tag{14}$$

We would like to additionally clarify the notation used in the case of a search in identity (14) above.

If the consumer chooses to search and $a \in Search$, then there must be corresponding values j and l denoting the brand and attribute chosen to search. Then, for the brand j intended for search under a, the value inside the exponential equals $v(\mu_{ijt}, \delta_{ijt+1})$, i.e. the value of searching j and attribute l once more. For all other brands $j' \neq j$, the value inside the exponential equals $v(\mu_{ij't}, \delta_{ij't})$. This expression follows the one for the benefit from searching displayed in equation (7).[20]

After each search action taken, the consumer observes a signal from the distribution $N(\mu_{ij}, \sigma_i^2)$. Therefore, in addition to consumer preference and search cost parameters, the specific history of the signals obtained up to time t can affect decisions at t. These signals are unobserved to the researcher, but will affect P_{iat}. Therefore, to integrate over the distribution of signals consumers obtain while searching, we draw S possible signal histories for each consumer, brand, and search, and average the resulting choice probabilities to form P_{iat}. Because these choice probabilities do not have a closed-form solution after averaging over signal draws, we will use the simulated log-likelihood function to estimate parameters. This function is given by

$$SLL = \sum_i \sum_a \sum_t d_{iat} log(P_{iat}), \tag{15}$$

where $d_{iat} = 1$ if consumer i chooses action a at t, and zero otherwise.

Recall that in our empirical setting, consumers search by moving their eyes to fixate on a different brand-attribute combination. Therefore, they search a lot: the average (median) number of searches equals 229 (186).[21] In particular, consumers search a lot more in our setting than in settings that prior work estimating a search model has looked at. In prior work, the number of searches rarely exceeds 3: number of searches is 2.96 in Honka and Chintagunta (2016) and Honka (2014), 1.2 in De los Santos et al. (2012), 2.3 in Chen and Yao (2017), 2.42 in Morozov et al. (2021), and 1.12 in Ursu (2018). Thus, in our setting, summing $log(P_{iat})$ over t for consumers for whom t is large (for example larger than 200) may result in a value for the likelihood function that approaches negative infinity. For details on how we address numerical issues that arise in our estimation, see Appendix 15.

Finally, we capture consumer heterogeneity in parameters using a latent class approach. We

[20]The second term in equation (14) follows from the expression for the expectation of the maximum of T1EV variables (see Train (2009), chapter 3.5, page 55 or Small and Rosen (1981)). We need to take this expectation, since, as researchers, we do not observe the utility error draws consumers observe when computing the maximum utility they will obtain from one additional search (the second maximum in equation (7)). Also, the expression for the maximum of T1EV variables contains a constant meant to represent the fact that utility is ordinal. In our estimation we will omit this constant, since it would only affect the scale of our estimates.

[21]Similarly, in our estimation sample, the average (median) number of searches equals 142 (131) – see Appendix 11.

hypothesize the existence of $N = 2$ segments, each with a different value for the parameters of interest. Using these parameters, we form variables of interest as above (prior mean, prior variance, signal mean, signal variance, and search costs) for each segment and compute P^n_{iat} for $n = \{1,2\}$. We then compute a weighted value of the P^n_{iat}'s using the probability of a consumer belonging to segment n (equal to $\pi_1 = exp(\rho)/(1+exp(\rho))$, with parameter ρ to be estimated) and obtain $P_{iat} = P^1_{iat} \times \pi_1 + P^2_{iat} \times (1-\pi_1)$. With P_{iat} in hand, we then follow the same steps as above to integrate over signal draws and form the simulated likelihood. By maximizing this simulated likelihood function, we are able to find the set of parameters that describe behavior in the case of consumer heteorogeneity. More details on this approach, as well as our general estimation routine can be found in Appendix 13.

5.5 Identification

In this section, we discuss how the parameters of our model are identified. We seek to identify three sets of parameters: (i) learning parameters, given by consumer prior beliefs ($\lambda_i, \beta_i, \gamma_i$), brand match values ($\mu_{ij}$), and signal variance ($\theta_i^2$); (ii) search cost parameters (κ_i, ω_i); and (iii) risk coefficient (r). Our data provide information on consumers' search decisions, i.e. what brand and what attribute they searched every fixation, their final brand choices, as well as survey information on consumer's prior information of these brands and their attributes. These data together with the decision rules in equations (6) and (7) constitute the essential components of our identification strategy.[22]

Learning parameters ($\beta_i, \gamma_i, \mu_{ij}$) are identified from the purchase probability of consumers with different information sets, similar to established identification arguments derived in prior work (Erdem and Keane (1996), Narayanan and Manchanda (2009), Ma (2019), Ursu et al. (2020)). More precisely, consumers who search very little make purchase decisions largely based on their prior beliefs. Therefore, the odds of purchasing Apple versus Nokia among consumers with limited search activity identify their prior beliefs (see Ursu et al. (2020)). For instance, observing that prior Apple owners who searched very little purchase Apple most often suggests that prior ownership plays an important role in driving consumer final choices (i.e. that β_i is positive). If instead such prior Apple owners frequently switched and bought other brands, then we would conclude that prior ownership plays a more limited role in consumer decisions. The same holds true for familiarity. In our model, familiarity affects consumers' prior uncertainty about a brand, and thus their utility. If brands consumers are more

[22]We note that our identification strategy depends on the one-step ahead decision rule we have assumed. We thank an anonymous reviewer to allowing us to acknowledge this point.

familiar with are purchased more often, then we would conclude that familiarity lowers uncertainty (i.e. that γ_i is positive) and plays an important role in affecting consumer choices. In contrast, when consumers search extensively, uncertainty converges towards zero and brand beliefs converge to the true match values. This allows us to estimate brand match values (μ_{ij}) from purchase frequencies of consumers who search extensively in a manner similar to that used in discrete choice models. For example, the odds of a consumer choosing to purchase Apple over Nokia after extensive search reveals her higher preference weight for this brand.

As is the case in all discrete choice models, only the relative level of utility is relevant for decisions. Therefore, we cannot identify all five brand intercepts in our model, i.e. we need to normalize the level of utility. To this end, we make the identifying assumption that brand values sum to one. Formally, this means that brand intercepts equal $\left[\mu_{i1}, \ldots, \mu_{iJ-1}, 1 - \sum_{j=1}^{J-1} \mu_{ij}\right]$, with brand J's value equal to 1 minus the sum of the values of all other brands (i.e. brand J serves as the reference brand and its value will not be directly estimated, but can be inferred based on the values of all other brands).[23] This assumption will allow us to pin down brand values in our model.

Consistent with prior work (e.g. Erdem and Keane (1996)), we assume the prior mean intercept λ_i equals the average brand value across the five brands in the experiment, i.e. $\lambda_i = \frac{\sum_{j=1}^{J} \mu_{ij}}{J}$. Under this assumption, we can interpret λ_i as consumer i's (mean) value of owning a smartphone. Given our identifying assumption that brand values sum to one, it follows that the value of λ_i simplifies as per $\lambda_i = \frac{1}{J}$. In other words, in our model the prior mean intercept will be constant across consumers and we will drop the i subscript moving forward. Also, as can be seen, knowing each brand's value a priori is not necessary to determine the value of the prior mean intercept, since this is given by the constant $\lambda = \frac{1}{J}$.

In our empirical specification, search costs vary across consumers i and attributes l (through consumers' prior experience level). The consumer specific mean search cost parameter k_i does not affect the selection or the choice rules (since it does not vary across brands or attributes) and is identified from the stopping rule. More precisely, from equations (6) and (7) we can see that the tradeoff between the expected utility (expected reduction in uncertainty) and the cost of searching determines when the consumer will continue rather than stop searching. As search progresses, uncertainty about the available options decreases, and thus the expected value of further reductions in uncertainty

[23] In Table B-6 (Appendix 10.3), we show that our results are robust to making a different assumption on the sum of the brand values – summing to zero, rather than one. We thank an anonymous reviewer for this comment.

diminishes (recall the diminishing returns specification of the utility function), while the mean search cost is unaffected by the number of searches. When the utility of continued search decreases to such a degree that it becomes lower than the search cost, consumers will stop search. Otherwise, they will choose to continue searching. Thus, the total number of searches a consumer performs will identify the range of mean search costs that must have made it beneficial for the consumer to perform the number of observed searches in our data. The level of mean search costs is identified by the functional form and the distribution of the utility function in equations (6) and (7) that define the value of continued search (for similar identification arguments, see Honka and Chintagunta (2016), Chen and Yao (2017), Ursu (2018), Ursu et al. (2020), Yavorsky et al. (2021)). Prior experience affects both the stopping and the selection rules since it varies across attributes l. Variation across consumers in their prior experience level and the prevalence with which those with higher prior experience search will identify the effect of prior experience from the stopping rule. For example, if consumers with a higher prior experience level stop their search earlier on average, then we can infer that prior experience has a negative effect on search costs (ω_i is negative). In addition, conditional on not stopping search, variation in the attributes chosen to search at every step will further pin down the effect of prior experience from the selection rule. For example, if attributes that consumers have a lot of experience with are searched less often, then we can infer a negative effect of prior experience on search costs.

As mentioned, the stopping rules in equations (6) and (7) reveal that consumers face a tradeoff between searching, which is costly but can further reduce brand uncertainty, and stopping to purchase the best option revealed so far. In our model, both low (mean) search costs (k_i) and potentially large expected reductions in uncertainty can encourage consumers to search a lot. At a moment in time, consumers differ in their search histories, as well as in the levels of their prior information (i.e. different prior ownership, familiarity) and this affects their expected reduction in uncertainty. Given this observed hetereogeneity, we can identify parameters for prior ownership and familiarity separately from the mean search cost, as explained above. The remaining challenge is identifying the effect on the expected reduction in uncertainty of the signal variance θ_i^2, parameter which does not vary across brands or attributes (similar to the mean search cost, k_i).[24] The separate identification of the signal

[24]We note that the main challenge in our model involves separately identifying mean search costs from the mean signal variance. Brand or attribute observables that would affect either search costs or the signal variance could be identified from observable variation in these variables in the data in some cases (as discussed in the previous paragraph and in Appendix 14 – e.g. when search costs are brand or attribute specific, while the signal variance only varies across consumers), but the identification argument would be more involved if the signal variance and search costs were both brand specific or brand and attribute specific. Nevertheless, in this section we discuss the identification of our model as specified.

variance follows from the selection rule. The selection rule dictates when the consumer should search the same option again and when she should switch to a different option. Regardless of the number of times a consumer searches the same option, her cost per search does not change (i.e. k_i is constant in t). Therefore, the mean search cost does not affect the selection rule. In contrast, the number of times a consumer searches the same option affects her expected utility, since the consumer observes a signal at every t with which she updates both her mean and variance beliefs (i.e. μ_{ijt} and δ^2_{ijt} depend on t). Therefore, the inherent randomness in the signal draw, the sequence of signals observed, together with consumers' search switching behavior will identify the effect of the signal variance θ^2_i on consumer searches, separately from the effect of mean search costs, which do not vary with the search sequence and which drop out of the selection rule. To see this, consider a consumer who searches option j at t and then switches to searching j' at $t+1$. At t, the consumer reveals that her expected reduction in uncertainty is higher than a threshold, which is a function of the utility of searching other options, such as j'. By switching to searching j' at $t+1$, the consumer reveals that her expected reduction in uncertainty from searching j is now lower than the same threshold, since the utility of options not searched (j') remains unchanged, not affecting the threshold. For a more formal demonstration of this argument, please see Appendix 14. Also, the same appendix sketches identification arguments for the two possible extensions of our model: brand-specific search costs and search costs that vary with t.

Because all the parameters in the prior mean, prior variance, signal mean and signal variance are estimated jointly, the risk parameter r will not be uniquely identified. Following the strategy in Erdem et al. (2005), we normalize r to 1, which maintains the assumption that consumers are risk averse.

5.6 Monte Carlo Simulation

To show that our model's parameters can be recovered using our estimation strategy, we performed the following Monte Carlo simulation exercise. We tried to mimic our data and generated consumers with different prior ownership (random binary variable with 60% probability of consumers owning a brand), familiarity with 5 brands, and prior experience with 7 attributes (both familiarity and prior experience are uniformly distributed on the interval from 0.1 to 1). We assigned one of the 5 brands as the reference brand and assumed the same mean brand effect for the remaining brands. Also, we generated data with 2,000 consumers.

In the simulation, consumers follow the same search and choice rules we described in equations

(6) and (7).[25] To integrate over all possible signal draws, we compute the likelihood function as an average over 100 draws from the signal distribution. Also, we perform the estimation exercise 200 times from different starting seeds and report results after averaging across these estimates. We also report the standard deviation of the mean estimate across these simulations.

Table 4 reports our results for the case where model parameters are homogenous. The first column displays the true coefficients we used to generate our data, while the second column shows our estimates. We find that our estimation strategy is able to recover parameters in our model well. In addition, in Table B-4 in Appendix 10.3 we present results with a different set of parameter estimates, once again showing that our estimation strategy performs well. Finally, in Table B-3 in Appendix 10.3 we report results that account for consumer heterogeneity using a latent class approach. Our estimation strategy is also able to recover heterogeneous model parameters well.

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Insert Table 4 about here

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In addition, we check the direction of the estimation bias arising when the researcher does not have data on any of the prior information variables we observe (prior ownership, familiarity, and prior experience), and is thus forced to assume that consumers do not vary in their prior information with the brands available. Concretely, this exercise involves generating data as above, assuming prior information affects model primitives, but estimating the model with β, γ and ω set to zero. In Table 4, column (3) we report our results. Table B-4 in Appendix 10.3 shows robustness in these results from a different set of parameter estimates.

We find that the brand value is overestimated, consistent with our results presented in Section 4, as well as in prior work (Shin et al. 2012). In other words, without data on prior information, the model interprets searches, that may actually be influenced by preference for a previously owned brand or by lower uncertainty due to familiarity, as motivated by valuable brand information obtained through search, inflating such brand preferences.[26] The intuition for these results is as follows. In the simulated data, there is a higher propensity to search and purchase brands with more prior information. However, without data on prior information, the researcher is forced to assume that prior beliefs do not vary across brands. Thus, a large number of searches on the same brand or a high propensity to

[25] Additional details about the data generating process can be found in Appendix 12.

[26] Because the data were simulated, there is no correlation between any of the variables used (e.g. between prior information variables). Therefore, our results cannot be explained by correlation in the data.

purchase a known brand will be interpreted to occur due to favorable brand signals observed through search, inflating brand intercepts. We also find that assuming away prior information leads to lower search cost estimates. In the simulated data, the observed high number of searches occurs in part because consumers like the brands they are knowledgeable about, not because they have low search costs. However, without data on prior information, the model estimates lower search costs in order to rationalize the same (large) number of searches. Finally, we also see an overestimation of the signal variance, arising to balance out the higher brand intercepts and lower search costs and explain the need to search. These results demonstrate the need to account for prior information when modeling consumer search and purchase decisions.

In this section, we presented results from estimating our model on simulated data. In the next section, we present our main estimation results using the data we presented in Section 3.

6 Estimation Results

Our results from estimating the model in Section 5 can be found in Table 5.[27] Also, in Appendix 10.2 we present additional estimation results under alternative specifications of the model. In addition, in Table B-5 in Appendix 10.3 we report results that account for consumer heterogeneity in all parameters using a latent class approach. Finally, in Table B-1 in Appendix 10.1, we report the misleading results we obtain from a model without learning (Weitzman 1979), where consumers are assumed to know the distribution of options they are searching for and thus not need to revisit a brand or its attributes.

In Table 5 column (1) we report the results from the model that uses survey data on consumers' heterogeneous prior information. In column(2), we report estimation results when we ignore consumers' heterogeneous prior information, by estimating our model with β, γ and ω set to zero. This exercise is meant to mimic the situation where the researcher does not have data on any of the prior information variables we observe in our survey, and is thus forced to assume that consumers have homogeneous prior information of the brands. The last column shows the effect of having partial information on consumers' prior information, i.e observing only prior ownership and familiarity, but not prior experience.

[27] In Appendix 11, we describe our estimation sample.

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Insert Table 5 about here

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Consider first the results that use survey data on consumer prior information (column (1) in Table 5).[28] In this case, we find that prior ownership is positive and significant, indicating that consumers place a higher value on the brand they own prior to commencing search.[29] Also, familiarity negatively impacts prior variance (positive effect on the inverse of prior variance; recall the expression in equation (9)), suggesting that the more familiar the consumer is with a brand, the lower her prior uncertainty. Both results are consistent with our reduced form evidence showing that brands consumers own and are more familiar with are more likely to be searched and purchased.

Our estimates of the signal mean (functions of brand intercepts) appear in the second panel of Table 5. We find that, compared to Nokia (the reference brand), all other brands have a larger brand value, with Samsung, Apple, and HTC providing a significantly greater value, consistent with their market shares. The signal variance is modest, which means consumers obtain relatively precise signals when searching, consistent with the large amount of prior information they possess about the brands before the experiment.

Search cost estimates are reported in the bottom panel of Table 5 and they show a significant effect. We find that prior experience with different smartphone functions decreases search costs. In other words, consumers who know more about certain smartphone attributes, for example the 'Battery' function, search those more efficiently.

Comparing these results with those in column (2), we can document the estimation bias arising from omitting data on consumer prior information from the model. We find that without data on consumers' prior information, the model would generally produce inflated brand preferences (consistent with our reduced form evidence presented in Section 4, with our Monte Carlo simulations, and with prior work, Shin et al. (2012)). More precisely, we find that when we assume away heterogeneity in consumer prior beliefs due to a lack of data, the model interprets searches, that may actually be influenced by preference for a previously owned brand or by lower uncertainty due to familiarity, as motivated by valuable brand information obtained through search. This effect is stronger for brands that have a

[28]We note that the standard errors of our estimates are typically smaller than those for the Monte Carlo simulation, due in part to differences in parameter values, the higher frequency of searches per consumer in our data, as well as the inherent randomness in the generation of simulated data.

[29]Due to high variation in the standard errors for prior ownership, we report the trimmed mean, excluding outliers larger than 1.

high share of prior ownership and high familiarity, namely Samsung and Apple. This is an important piece of evidence that supports the need to account for consumers' prior information in modeling search and purchase decisions. Without such data, estimated parameters, as well as their implications for marketing strategy may be biased. Comparing the two models in Table 5 in terms of log-likelihood, AIC and BIC measures, we find that using our survey data on prior information improves fit.

In addition, we find that search costs are underestimated when prior information is omitted from the model. Comparing these results to those in column (3) we find that this effect is not solely driven by the absence of a (negative) effect of prior experience on search costs: even when we omit prior experience from the model, but account for prior ownership and familiarity, we obtain higher search cost estimates than in the model that omits prior information. This result can be understood as follows. The high number of searches we observe occurs in part because consumers like the brands they own and are familiar with, not because they have low search costs. However, without prior information data, the model mistakenly attributes repeated searches of a brand to low search costs.

We also find an overestimation of the signal variance when not accounting for prior information (comparing columns 2 and 1). Assuming away belief heterogeneity makes it seem like consumers' posterior uncertainty remains high after every search, lowering the utility of a brand. This estimation result arises to balance out the higher brand intercepts and lower search costs and rationalize the search and choice patterns we observe. Instead, we find that signal variance is lower when accounting for prior information and that signals obtained through search are a lot more precise, but that this relation cannot be captured without data on prior information. Therefore, once more we demonstrate the importance of accounting for prior information.

We note that our data on prior information does not capture all necessary aspects describing consumer prior beliefs. Other measures of liking, awareness, search histories, or intention to buy may be obtained to reveal a more complete picture of consumer prior beliefs. To show the value of obtaining only partial information on prior information, in column (3), we include only prior ownership and familiarity in the model, and exclude prior experience. Companies have relatively easy access to data on brand prior ownership and familiarity. Prior ownership is available from purchase histories revealing which consumers have purchased before and which consumers are new to the brand. Also, brand familiarity is tracked frequently by marketing research companies, for example through consumer surveys or search/browsing histories. We find that even with partial prior information data we can lower the estimation bias: brand preferences are lower, search costs are higher, and the signal variance is lower. This evidence further supports the value of prior information data.

Finally, in Table B-5 in Appendix 10.3 we account for heterogeneity in all parameters using a latent class approach. We find that segments are relatively similar in their brand preferences, as well as their prior ownership and familiarity effects, but differ substantially in their prior experience with smartphone functions and in their search costs. Segment 1, which is relatively larger, though not significantly so (53% of the consumers, obtained from the calculation $exp(0.1344)/(1+exp(0.1344)))$, has higher search costs, but searches smartphone functions that it is more experienced with more often, leading to a large effect of prior experience on search costs. Segment 2 has lower mean search costs, and it tends to search attributes that it is less experienced with more often. One possible interpretation of this result is that consumers with high search costs find it more efficient to focus their search on attributes that they are more experienced with, while those with lower search costs can inspect new attributes as well. Finally, we find that extending the latent class model to two segments leads to a modest improvement in fit compared to the homogeneous parameter model (the AIC decreases to 171,390 and the BIC decreases to 171,552).

In conclusion, our estimation results show how prior information impacts consumers' search and purchase decisions. When we do not use data on consumers' prior information, model estimates may be biased.

7 Counterfactuals

In this section, we present the results of a series of counterfactual exercises that explore the value of using information on consumer priors to improve marketing strategies. Towards this end, we use our estimation results from column (1) in Table 5 to simulate search patterns and final brand choices. To integrate out of the signals that consumers obtain while searching, we replicate the simulation 100 times and report average results.

First, we explore the effects of removing prior information on brand market shares. In other words, we ask if consumers had no prior information on the brands available and their attributes, would they purchase the same brands? We consider three scenarios: (i) consumers do not own any of the five brands, (ii) consumers have no prior familiarity with the brands, and (iii) consumers have no prior experience with brand attributes. These scenarios are meant to capture behavior in cases where consumers are making choices in a new product category, among new brands/products, or among products with new features. Also, these are meant to quantify the managerial value of prior information for brand choices.

Our results from this first counterfactual can be found in Figure 6, where we report percent changes in market shares across brands and scenarios. In general, we find that, regardless of the source of the prior information, removing this information hurts Samsung and Apple, while benefiting all other brands. Consequently, if consumers had no prior information on the brands available, then market shares would be more homogeneous across brands.

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Insert Figure 6 about here

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To understand these results, we will analyze in turn the effect of removing each source of information on market shares. First, consider the case where consumers have no prior ownership of either of the five brands. Our estimation results (Table 5) show that prior ownership positively affects the prior mean and thus has a direct and positive effect on consumer final choices. In other words, brands consumers have previously owned are more likely to be purchased. Therefore, Samsung and Apple, the brands that in our data were most frequently owned prior to our study, suffer the most (as much as a 1.4% decrease in market shares) when prior information is removed, while all other brands see an increase in market shares. This effect is largest for the brand that is least frequently owned, Nokia, showing an increase of more than 1% in market shares.

Second, consider the case where consumers have no prior familiarity with the brands. As we have shown in Table 5, familiarity has a negative effect on the prior variance, i.e. familiarity with a brand decreases uncertainty. Therefore, if consumers had no prior familiarity with the brands, then they would start their search with higher uncertainty, needing to search more, and thus potentially finding different brands to buy. Once again, we find that brands that consumers were previously relatively more familiar with, such as Samsung and Apple, are hurt the most, while the least familiar brands are benefited by the fact that consumers are willing to search them more. For example, Apple's market share decreases by 1.2%, while HTC's market share increases by 1.9%. Motorola is also hurt in this case given its high prior familiarity level (third most familiar brand in our data).

Third, suppose consumers had no prior experience with brand attributes. Prior experience has a negative effect on search costs (see Table 5). Thus, when prior experience is removed, consumer search costs increase, and thus total searches decrease (a decrease of 17%). When total searches decrease, we expect that brands that were previously searched most often, such as Samsung and Apple, to be hurt the most, which is what Figure 6 reveals. In addition, the size of the effect depends on the attributes of these brands. For example, Samsung scores higher than Apple on attributes that consumers care most about, such as battery and memory (see Table 2), and is thus hurt relatively more.

Our second counterfactual asks how familiar do consumers have to be with a brand so that its effect compensates for the lack of prior brand ownership?[30] In other words, if a consumer has not owned a brand/product before, can the firm increase familiarity and compensate for this lack of ownership? Companies can affect consumer familiarity through their advertising decisions. Evidence from both academic papers and industry reports shows this link. For example, there is a plethora of papers in Economics and Marketing showing that advertising has primarily an informative role, i.e. advertising makes consumers aware of more brands, increasing their familiarity with these brands and thereby consumers' overall information about the market. A non-exhaustive list of such papers includes: Ackerberg (2001, 2003), Clark et al. (2009), Terui et al. (2011), Blake et al. (2015), Tsai and Honka (2018), Honka et al. (2017). In addition, several non-academic resources instruct companies to create brand awareness and familiarity.[31] In such industry reports, managers are reminded of the purchase funnel and of the importance of investing in awareness since brands consumers are unaware of cannot be considered or chosen. Tying this fact with the academic results above reveals the ability and usefulness of using advertising to increase awareness, brand familiarity and thus consumer prior information.

We expect the answer to the question of whether firms can increase familiarity to compensate for a lack of prior ownership to vary across brands. Thus, in Figure 7 we show the answer to this question for each brand in turn. In our first scenario, we look at the impact of consumers not owning a focal brand. Note that this counterfactual differs from our first counterfactual since here we allow consumers to still own other brands than the focal brand. Then, in our second and third scenarios we consider whether investments in familiarity by the focal brand compensate for its lack of prior

[30] We focus on familiarity because it is the only measure of prior information in our data that companies can influence directly, for example through advertising. Although brands can advertise smartphone attributes as well, our measure of prior experience with attributes captures usage of, rather than only information about these attributes. Therefore, we expect to see changes in our measure of prior experience only if consumers buy a smartphone with new features, which we assume brands cannot affect directly. For this reason, we do not report results of a counterfactual where brands influence attribute experience.

[31] For examples, see https://www.linkedin.com/pulse/familiar-why-brand-familiarity-key-becoming-powerful-larry-light, https://www.ft.com/content/5d4518ea-87c5-3053-a96f-d288f3b51c72, https://econsultancy.com/82-percent-searchers-choose-familiar-brand-search/.

ownership.

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Insert Figure 7 about here

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Consider first the case of Samsung. If consumers did not own any Samsung products before beginning their search, but owned other brands, then Samsung's market shares would be more than 2.4% lower – a larger effect than in the first counterfactual where no consumers owned any brands before the experiment. This effect is large and cannot be fully compensated for by investments in familiarity. More precisely, if Samsung increased its familiarity by 20%, it would recover only less than 0.3% of its market share (13%). Even increasing familiarity of all consumers to the maximum value of 7 would only allow Samsung to recover approximately half of its lost market share. This happens because Samsung is already one of the most familiar brands, so additional increases in familiarity have only a moderate effect. We see a similar result in the case of Apple where any amount of familiarity would not be able to compensate for the lack of prior ownership.

Finally, if we consider the other three brands that are even less familiar to consumers, we find the opposite effect: a lack of prior ownership has a small effect on market shares and investments in familiarity can more than compensate for this effect. For example, if no consumers owned Nokia, then its market share would be marginally affected (less than 0.1% lower), but increasing familiarity to the maximum level leads to more than a 3% increase in market shares. Similar results hold for HTC and Motorola.

We view these results as adding to our understanding of the managerial value of prior information and helping companies decide when and whether to invest in increasing consumer familiarity given consumers' current level of information. We find that the marginal benefit of increasing familiarity (e.g. through advertising) decreases with an increase in prior ownership, i.e. brands that consumers own frequently will benefit less from each investment in familiarity (e.g. Samsung recovers only a fraction of its lost market share by increasing familiarity by 20%, while Nokia more than compensates for the lost market share). This result implies that prior ownership constitutes that the best kind of advertising for top brands.[32]

In conclusion, in this section we have shown that, in addition to recovering more precise estimates of consumer primitives, accounting for brand-specific prior information also benefits managers by

[32]We are grateful to the Associate Editor for this insightful observation.

allowing them to use this information to improve marketing decisions.

8 Discussion

In this paper, we aimed to quantify the role of information consumers possess prior to search on their search and purchase decisions. Towards this end, we developed a search model in which both the information obtained during the search process and the information possessed by consumers prior to search were allowed to influence search and purchase decisions. We estimated this model on a data set of consumers making smartphone search and purchase decisions that allowed us to observe consumers' prior brand ownership, familiarity and prior experience with smartphone attributes. We showed that prior information impacts consumer search and purchase decisions in three ways: (1) prior ownership of a brand increases the initial evaluation of the brand; (2) prior familiarity with the brand decreases initial uncertainty; and (3) prior experience decreases search costs. Also, we have documented the direction of the estimation bias arising if data on prior information is not available when modeling consumer search and purchase decisions. Finally, using our estimation results, we performed a series of counterfactual exercises and showed the managerial importance of using and investing in consumer prior information.

This paper can be extended in a number of directions. One direction may involve considering different heuristics that consumers may use while searching. At another extreme, one can attempt to derive search rules for our problem assuming consumers optimally look $n > 1$ steps into the future, in order to compare model fit. Also, future work could investigate the role of prior information in affecting decisions over a longer time frame when forgetting may play an additional role. One limitation of our study is its reliance on a single data set, where consumers used a product comparison website to make smartphone search and purchase decisions. While our focus helps us examine the impact of prior information in a well-controlled experimental environment, this setting may be narrow compared to other consumer search settings. Therefore, studying the importance of prior beliefs across a larger range of both product categories and information environments would be recommended.

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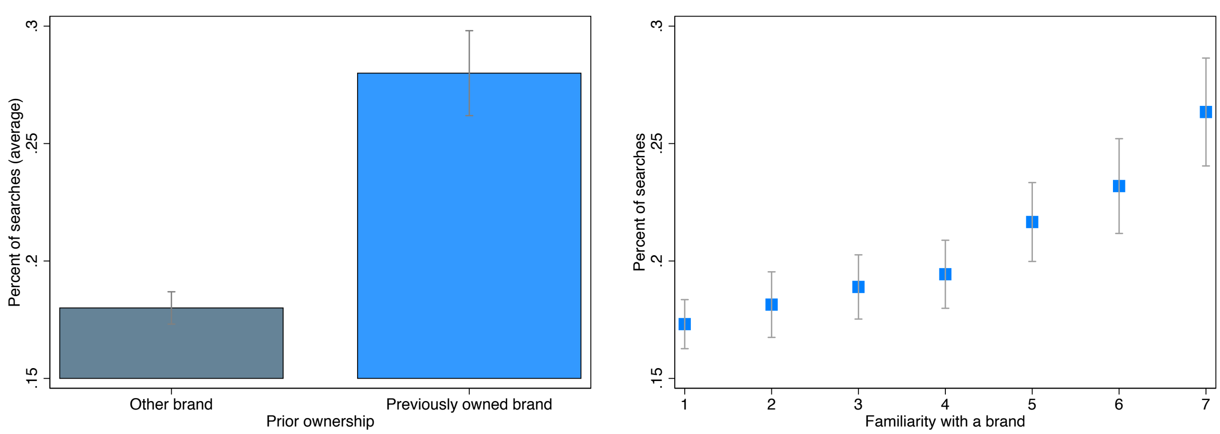
Figures and Tables

<table>
<tr><th></th><th></th><th>Apple iPhone 5</th><th>HTC One</th><th>Samsung Galaxy Note II</th><th>Nokia Lumia 920</th><th>Motorola Droid RAZR MAXX HD</th></tr>
<tr><td></td><td>Colors Available</td><td>Click to Buy</td><td>Click to Buy</td><td>Click to Buy</td><td>Click to Buy</td><td>Click to Buy</td></tr>
<tr><td>Price</td><td>Price with 2-year Contract</td><td>$249.99</td><td>$199.99</td><td>$249.99</td><td>$99.99</td><td>$199.99</td></tr>
<tr><td rowspan="3">Wireless Capabilities</td><td>Band and Mode</td><td>|EDGE|GSM|Quad-band GSM|3G|UMTS|Quad-band UMTS|HSPA+|HSDPA|CDMA|4G LTE|Dual-band LTE|</td><td>|EDGE|GSM|Quad-band GSM|GPRS|3G|UMTS|HSDPA |CDMA|4G|4G LTE|Dual-band LTE|</td><td>|GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|Dual-band LTE|Quad-band|</td><td>|EDGE|GSM|Quad-band GSM|3G|Quad-band UMTS|HSPA+|HSDPA|4G|4G LTE|Dual-band LTE|</td><td>|EDGE|GSM|Quad-band GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|</td></tr>
<tr><td>Bluetooth</td><td>4.0</td><td>4.0</td><td>4.0</td><td>3.0 + HS</td><td>4.0</td></tr>
<tr><td>WiFi</td><td>802.11 a/b/g/n</td><td>802.11 a/b/g/n/ac</td><td>802.11 a/b/g/n</td><td>802.11 a/b/g/n</td><td>802.11 a/b/g/n</td></tr>
<tr><td rowspan="2">Operating System (OS) and Other Features</td><td>Mobile Operating System</td><td>iOS 6</td><td>Android 4.1 Jelly Bean</td><td>Android 4.1 Jelly Bean</td><td>Windows Phone 8</td><td>Android 4.1 Jelly Bean</td></tr>
<tr><td>Supported Email</td><td>POP3, IMAP, Push email (Exchange, Gmail)</td><td>POP3, IMAP, Push email (Exchange, Gmail, Hotmail)</td><td>POP3, IMAP, Push email (Exchange, Gmail)</td><td>SMTP, POP3, IMAP4, Push email (Exchange, Gmail, Hotmail)</td><td>POP3, IMAP, Push email (Exchange, Gmail)</td></tr>
<tr><td rowspan="2">Size</td><td>Product Dimensions</td><td>4.87" x 2.31" x 0.30"</td><td>5.41" x 2.69" x 0.37"</td><td>5.95" x 3.17" x 0.37"</td><td>5.13" x 2.79" x 0.42"</td><td>5.19" x 2.67" x 0.37"</td></tr>
<tr><td>Product Weight</td><td>3.95 oz.</td><td>5.04 oz.</td><td>6.44 oz.</td><td>6.53 oz.</td><td>5.54 oz.</td></tr>
<tr><td>Display</td><td>Screen Size</td><td>4.0 inches</td><td>4.7 inches</td><td>5.5 inches</td><td>4.5 inches</td><td>4.7 inches</td></tr>
<tr><td rowspan="2">Battery</td><td>Standby Time</td><td>Up to 9 days</td><td>Up to 20 days</td><td>Up to 19.5 days</td><td>Up to 13 days</td><td>Up to 16 days</td></tr>
<tr><td>Talk Time</td><td>Up to 8 hours</td><td>Up to 18 hours</td><td>Up to 21 hours</td><td>Up to 7.5 hours</td><td>Up to 32 hours</td></tr>
<tr><td>Camera</td><td>Camera Resolution</td><td>8.0MP</td><td>HTC UltraPixel 4MP Camera</td><td>8.0MP</td><td>8.7MP</td><td>8.0MP</td></tr>
<tr><td rowspan="3">Memory</td><td>Internal Memory</td><td>32GB</td><td>32GB</td><td>16GB</td><td>32GB</td><td>32GB</td></tr>
<tr><td>Memory Card</td><td>No</td><td>No</td><td>microSD up to 64GB</td><td>No</td><td>microSD up to 32GB</td></tr>
<tr><td>RAM</td><td>1GB</td><td>2GB</td><td>2GB</td><td>1GB</td><td>1GB</td></tr>
</table>

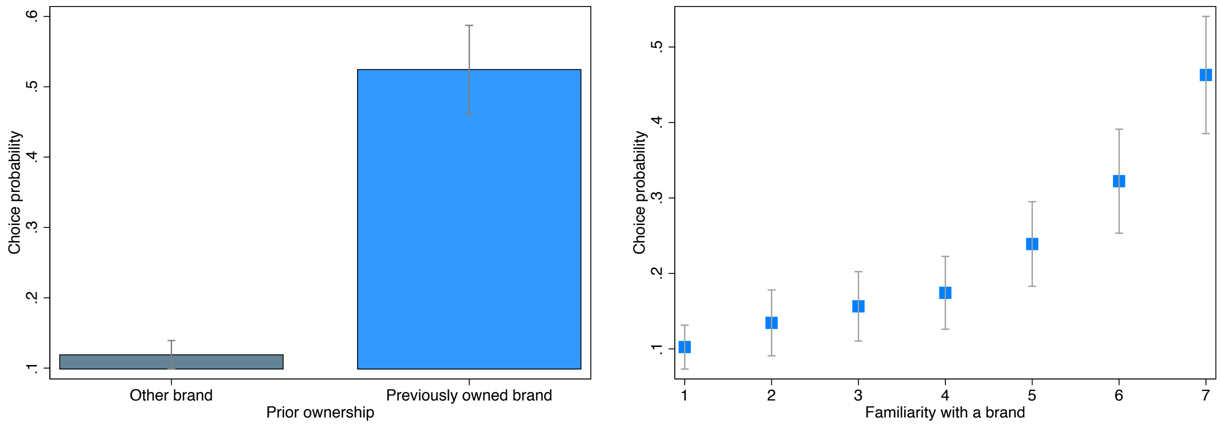
Figure 1: Experiment design under the low complexity condition



(a) Prior ownership

(b) Familiarity

Figure 2: Percent of brand-level searches as a function of prior information



(a) Prior ownership

(b) Familiarity

Figure 3: Choice probability as a function of prior information

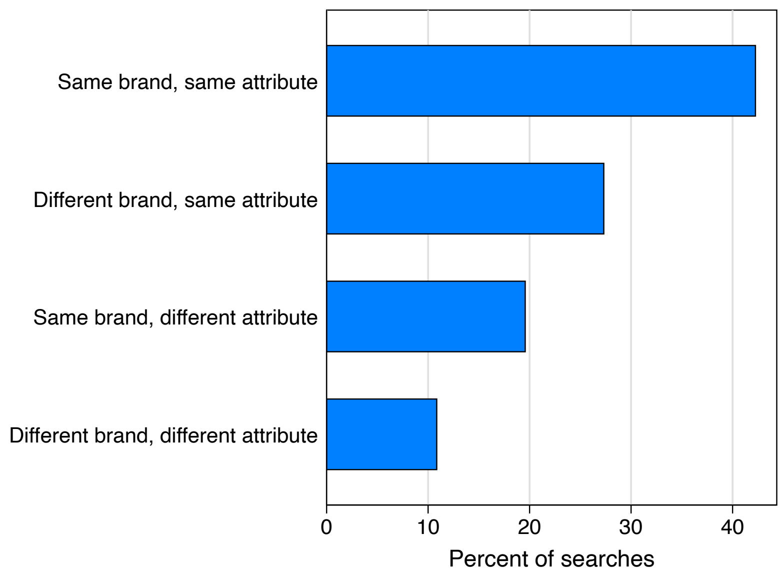
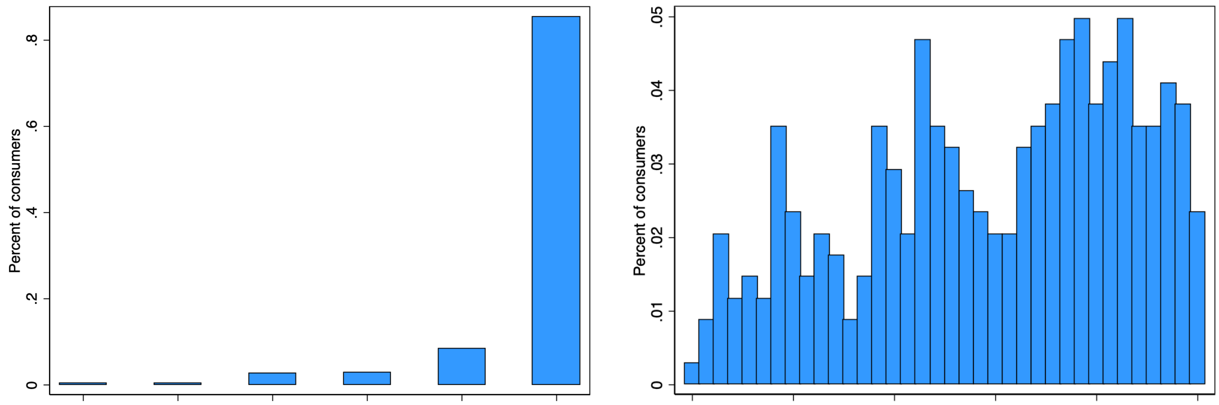


Figure 4: Percent of searches on different brand-attribute combinations



(a) Percent of brand revisits **(b) Percent of brand-attribute revisits**

Figure 5: Search revisits

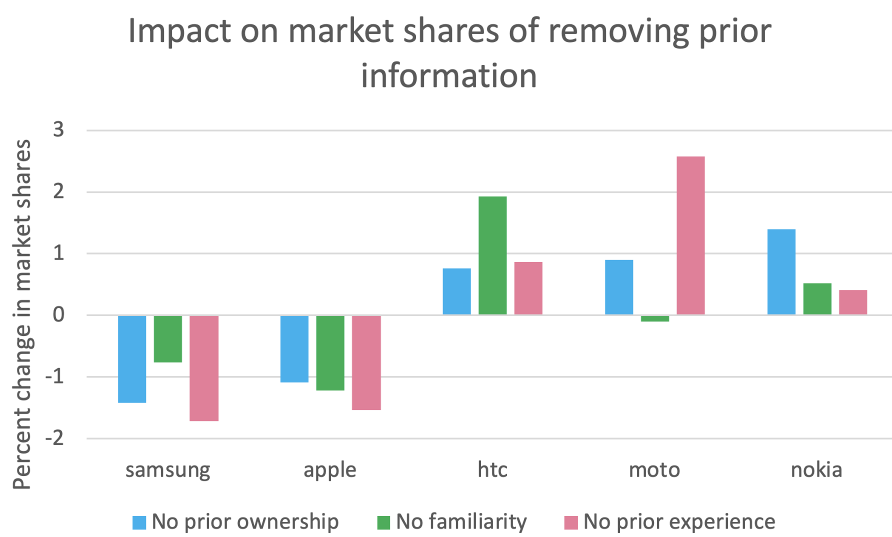


Figure 6: Counterfactual 1– Effect of no prior information

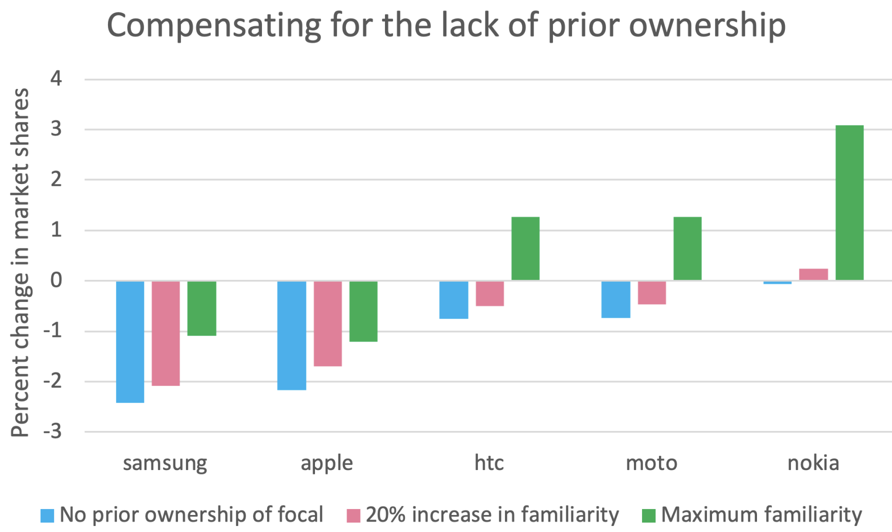


Figure 7: Counterfactual 2 – Compensating for brand specific no prior ownership

Table 1: Consumer prior ownership and familiarity

Brand	Prior Ownership %	Avg. Familiarity	Std. Dev. Familiarity
Samsung	24.27	4.20	1.96
Apple	29.53	4.76	1.83
HTC	11.11	2.88	1.86
Motorola	6.43	3.11	1.80
Nokia	0.58	2.41	1.60
Others	7.31		
None	20.76		

Notes: Prior ownership identifies the brand of smartphone the consumer owns at the time of the study. Familiarity is measured on a scale from 1 to 7 where 1 corresponds to 'Not at All' and '7' corresponds to 'Extremely Well'.

Table 2: Consumer prior experience with brand attributes

Statistic	N	Mean	Std. Dev.	Min	Pctl(25)	Pctl(75)	Max
Technical	342	0.447	0.281	0	0.3	0.7	1
Size	342	0.500	0.339	0	0.2	0.8	1
Camera	342	0.446	0.309	0	0.2	0.7	1
Battery	342	0.706	0.409	0	0.4	1	1
Memory	342	0.529	0.358	0	0.1	0.8	1

Notes: The original responses were converted to numeric values ranging from 0 to 1, where 0 corresponds to 'Never' and '1' corresponds to 'Several Times Per Day'.

Table 3: Effect of prior information on brand level searches and choices

	Percent of brand searches (OLS)		Brand choice (Clogit)		
	(1)	(2)	(3)	(4)	(5)
Brand value					
Samsung	0.0799***	0.0519***	1.3471***	0.4607	0.1121
	(0.0101)	(0.0099)	(0.2201)	(0.2397)	(0.3071)
Apple	0.0528***	0.0176	1.2192***	−0.0086	0.0670
	(0.0099)	(0.0100)	(0.2232)	(0.2608)	(0.3307)
HTC	0.0416***	0.0313***	1.0324***	0.7186**	0.5210
	(0.0086)	(0.0085)	(0.2284)	(0.2372)	(0.3060)
Motorola	0.0162	0.0076	0.7492**	0.3937	0.4064
	(0.0087)	(0.0086)	(0.2380)	(0.2463)	(0.3208)
Nokia	-	-	-	-	-
Prior information					
Prior ownership		0.0685***		0.8453***	0.7527***
		(0.0110)		(0.1537)	(0.2087)
Familiarity		0.0459***		2.6367***	2.5313***
		(0.0093)		(0.3719)	(0.4776)
Search					
Percent of brand searches					13.5021***
					(1.0013)
R^2	0.0520	0.1074			
LL			-523	-449	-249
AIC			1,053	910	511
BIC			1,075	943	550
Observations	1,710	1,710	1,710	1,710	1,710

Standard errors in parentheses

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

Notes: Effect of brand value and prior information on searches (OLS) and choices consumers made (conditional logit at the consumer level). Standard errors in specifications (1) and (2) are clustered at the consumer level. The constant in the regressions in specifications (1) and (2) is omitted. The reference brand is Nokia. Familiarity was rescaled by dividing by the maximum value - this rescaling makes it comparable with other variables included in the analysis. The number of observations equals 1,710, resulting from 5 brands that each of the 342 consumers could search.

Table 4: Monte Carlo simulation results

	True	*With Prior Information* Estimate	*Without Prior Information* Estimate
	(1)	(2)	(3)
Prior mean			
Prior Ownership	2.00	1.9488	-
		(0.6457)	
Prior variance			
Familiarity (inverse)	1.00	1.0197	-
		(0.4135)	
Signal mean			
Brand Value	1.00	1.1061	1.1715
		(0.2565)	(0.3172)
Signal variance			
Constant	1.00	1.2570	3.6409
		(0.7776)	(2.4050)
Search cost (exp)			
Constant	-1.00	-0.9913	-1.7921
		(0.0520)	(0.2838)
Prior Experience	-2.00	-1.9591	-
		(0.2667)	
Observations		63,084	63,084
LL		−227,190	−227,277

Notes: Data is simulated for 2,000 consumers, 5 brands and 7 attributes and the reported estimation results are obtained after averaging across estimation results from 200 different seeds, with 100 signal draws each. The standard deviation of the mean estimate across these simulations is reported in parentheses. The number of observations varies slightly across seeds, with the number reported above representing the average number of observations.

Table 5: Estimation results

	With Prior Information	*Without Prior Information*	*Partial Prior Information*
	(1)	(2)	(3)
Prior Mean			
Prior ownership	0.3734***		0.3757***
	(0.0396)		(0.0506)
Prior Variance			
Familiarity (inverse)	0.6115***		0.6775***
	(0.0225)		(0.1488)
Signal Mean			
Samsung	0.2655***	0.5174***	0.4488**
	(0.0107)	(0.0448)	(0.1458)
Apple	0.4116***	0.5700***	0.4499*
	(0.1123)	(0.1320)	(0.1998)
HTC	0.2028**	0.2535***	0.2051
	(0.0700)	(0.0537)	(0.1460)
Motorola	0.1301^{+}	0.1963	0.1681
	(0.1000)	(0.1667)	(0.1969)
Nokia	-	-	-
Signal Variance			
Constant	0.3348***	0.7022***	0.4488***
	(0.0148)	(0.0410)	(0.0707)
Search Cost (exp)			
Constant	−0.3910***	−2.0883***	−1.5386***
	(0.0015)	(0.0462)	(0.0236)
Prior Experience	−0.5668***		
	(0.0108)		
LL	−85,765	−86,057	−86,083
AIC	171,548	172,127	172,182
BIC	171,624	172,178	172,250
Observations	36,170	36,170	36,170

$^{+}$ ($p < 0.10$), * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$)

Notes: The results are averaged over 10 estimations using different starting seeds, with 50 signal draws each.