Simultaneous or Sequential? Search Strategies in the U.S. Auto Insurance Industry

Elisabeth Honka[1]

University of Texas at Dallas

Pradeep Chintagunta[2]

University of Chicago Booth School of Business

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Abstract

We explore whether the search strategy consumers use is identified in cases where researchers observe consumers' consideration sets (but not the sequence of searches) in addition to their purchases, price distributions, prices for the considered alternatives and other characteristics. We show that the search method is identified by the difference in the pattern of actual prices in consumers' consideration sets across the two methods. Next, we provide an approach to estimating the parameters of a sequential search model with these data; thereby complementing earlier work that has estimated a simultaneous search model with such data. We then undertake a comprehensive simulation study to understand the implications of making an incorrect assumption on search method for model fit and estimated parameters. Conditional on our assumed functional form for consumers' utility functions, we find that the correctly specified model recovers the true parameters. The incorrect search model is unable to reflect the price patterns corresponding to the correct specification leading to an inferiror fit to the data in all simulation replications. We extend our simulations to examine several assumptions made in the empirical literature on search. Next, using a novel data set on consumer shopping behavior in the U.S. auto insurance industry that contains information on consideration sets as well as choices, we look at the patterns in the price data to see whether the data are consistent with simultaneous or sequential search. We then study the consequences of assuming either sequential or simultaneous price search on consumers' estimated preferences, price sensitivities and search costs. Our model-free evidence suggests simultaneous search and the simultaneous search model also provides a better fit to the data than the sequential model. We find consumer search costs of $42. A sequential search model results in very different estimates of consumers' preference parameters. We also explore the implications of our results for insurance companies and for consumers. We find that the largest insurance companies are better off when consumers search sequentially, while smaller companies profit from consumers searching simultaneously.

[1]Email: elisabeth.honka@utdallas.edu.

[2]Email: pradeep.chintagunta@chicagobooth.edu.

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1 Introduction

Understanding the nature of consumer search behavior is vital to a better understanding of how consumers form consideration sets and ultimately make choices in categories with multiple options. A consumer who engages in search is uncertain about some dimension(s) of the product or service, say price, and resolves this uncertainty by incurring a search cost. In the search process, the consumer trades off the costs incurred and benefits accrued from the undertaking to arrive at a set of options for which he has complete information. At this stage, the consumer is back to the familiar choice situation of complete information that has been extensively studied in the marketing literature (e.g., the brand choice literature using scanner panel data). If a consumer incurs a marginal cost for each product or service searched, then the number of options the consumer ends up considering before making a choice critically depends on the search strategy the consumer uses.[3] Under a fixed- or simultaneous-search strategy, the consumer samples a fixed number of alternatives and purchases the alternative with the lowest price (or highest utility) in this set. The number of alternatives searched is obtained by looking at the subset for which the expected maximum utility net of search costs is the highest among all possible subsets.

A limitation of the simultaneous search strategy is that it does not take into account new information that the consumer might obtain during the search process. So if the consumer observes a very low price (or very high utility) for an alternative early in the search process, the benefit from an additional search may be below the marginal cost of that search (see Baye et al. 2006). In a sequential search strategy on the other hand, the number of alternatives searched is not fixed but is a random variable which depends on the outcome of the search; this allows a consumer to economize on information costs. In this case, the consumer weighs the expected benefits and costs of gathering additional price information after each new price quote is obtained. If an acceptable price is obtained early on, the expected gains from additional searches are small and there is no need to pay the cost of additional searches (Baye et al. 2006).

Whether consumers search simultaneously or sequentially has therefore long been a question of interest to researchers. Since in most instances researchers only observe variation in prices or purchase outcomes, it is not possible to identify the search method with just these data. Previous empirical research has circumvented this challenge by explicitly assuming the type of search that consumers engage in. For example, Mehta et al. (2003), Pires (2012), Honka (2013) and Muir et al. (2013) assume that consumers search simultaneously, while Dahlby and West (1986), Hortacsu and Syverson (2004), Kim et al. (2010), and Allen et al. (2012) assume that consumers search sequentially. In this paper, we focus on the case where the researcher observes each consumer's consideration set (but not the sequence of searches), besides purchase outcomes, prices and

[3] A search cost is an information "cost" borne by a consumer to acquire information about a firm - usually in the form of time and effort required to obtain such information. It does not have to be a monetary cost.

other characteristics. We show that, under certain assumptions, the search method is indeed identified by the price patterns in consumers' observed consideration sets. Specifically, under simultaneous search, we show that consumers' consideration sets contain a constant proportion of below and above average prices across all consideration set sizes and across all consumers.[4] This is because consumers make the decision on which and how many companies to search beforehand and do not react to price draws in terms of adjusting their search behavior. Under sequential search, consumers stop searching as soon as they get a sufficiently low price draw. Thus, holding everything else constant, we only expect consumers to search a lot when they get a sequence of relatively high price draws and as a consequence the proportion of below average price draws decreases as consumers' consideration sets increase in size. Our identification strategy holds for a very broad range of settings that we discuss in detail in the Identification section. For the homogeneous goods case, we also show that there is a second data pattern identifying the search method, namely, that the proportion of consumers searching a specific number of times declines as the number of searches increases.

Next, we examine the consequences of imposing an incorrect assumption on search method on the estimated preference and search cost parameters of consumers when researchers have access to the above data. To accomplish this, we first need an estimation approach for the sequential search model where the researcher has access to individual-level data on consideration sets, purchases and other characteristics, but not the sequence of searches. While initially one might think that in such a situation all possible search sequences have to be enumerated and evaluated - a very cumbersome approach in markets with many alternatives - we suggest a different estimation approach in which we place a small set of restrictions on consumers' utilities and reservation utilities. These restrictions are derived from Weitzman's (1979) search, stopping and choice rules and the insight that, in addition to Weitzman's (1979) rules, it must have been optimal for the consumer *not* to stop searching and purchase earlier. Similar to the simultaneous search model for which we apply a simulated MLE (SMLE) estimation approach suggested by Honka (2013), we propose an SMLE-based approach for the sequential search model.

To illustrate data patterns under the two search methods, search method identification and our new estimation approach for sequential search, we conduct an extensive set of simulation studies. We generate individual-level data in which all consumers search either simultaneously or sequentially.We then estimate a set of search models for which the researcher knows (does not know) the true search method consumers use. First, we find that our proposed approach to identifying the search method with price patterns from consideration sets works well with simulated data. We find that our newly proposed sequential search model estimation approach is able to recover the true model parameters; in general the correctly specified search

[4] I.e., the actual price of each alternative in the consideration set lies below the mean price of the price distribution of that alternative with probability λ.

model recovers the true parameters whereas the incorrectly specified one does not. Our simulation also shows that the incorrectly specified model results in an inferior fit to the data in *all* replications of the simulation and for both search methods. This supports the findings based on identification of the search method using price patterns - the incorrectly specified model cannot reflect the price patterns in the simulated data.

We then provide an empirical application of our search method identification and new sequential search estimation approach. Using data on consumers' consideration sets, purchases, prices and other characteristics we try to answer the question: do households search simultaneously or sequentially? In our empirical application using consumer data from the auto insurance industry, we first look for model-free evidence for a search method and then estimate the model parameters under the assumptions of simultaneous and sequential search. We find both the model-free evidence and the estimates to provide support for the simultaneous search model. We find search costs of around $42. We then study via counterfactuals whether some companies win or lose when consumers change their search method (due e.g., to changes in accidents, credit scores etc.) and how their customer bases are affected as a consequence. We find that the largest insurance companies are better off when consumers search sequentially, while smaller companies profit from consumers searching simultaneously.

The main contributions of the paper are as follows. First, we show both analytically and through simulations that the search method consumers use is identified by the price patterns in consumers' consideration sets for a very broad range of settings. Further, for the homogeneous goods case, we show that there also is a second identifying data pattern. Second, we provide a comparison of the consequences of assuming simultaneous versus sequential search strategies in contexts where the only data available to researchers besides typically available choice data are information on consumers' consideration set compositions. This kind of data are becoming more widely available across a variety of service businesses as well as from surveys conducted by firms such as JD Power for a variety of categories (e.g. automobile purchases, hotels and retail banking). Third, in providing such a comparison, we need to be able to estimate model parameters under both search assumptions for these kind of data. While Honka (2013) provides an approach for simultaneous search that we adopt here, we propose an approach for estimation under the sequential search assumption. Fourth, we provide extensive simulations to show that conditional on the assumed model structure, our estimation methods can recover true model parameters. Importantly, under our model structure assumption, the simulations also show that model fit is an appropriate criterion to use to choose the search method generating the data reflecting the inability of the incorrectly specified model to replicate the price patterns in the consideration set data. Fifth, we also quantify the effects of changing the search method and its implications for consumers and firms.

In the next section, we discuss the relevant literature. In section 3, we introduce our model and in section

4 we describe our estimation approaches. In section 5, we discuss identification and present Monte Carlo studies in the following section. Then we discuss our empirical application and study several counterfactuals. We close our paper by discussing its limitations and future research opportunities and finally conclude.

2 Relevant Literature

Our paper is embedded in the literature on consumer search. In a recent paper, De los Santos et al. (2012) investigate whether the type of search can be identified when the sequence of searches is observed. They find for the case of one distribution of prices in the market that consumers should always purchase the brand they searched last under sequential search. With a "full" utility specification, i.e. one which contains brand intercepts, advertising, price and possibly an error term, and/ or company-specific price distributions, De los Santos et al. (2012) find that under sequential search a consumer's decision to continue searching should depend on observed prices, i.e. consumers who observe a relatively high price in the company's price distribution should be more likely to continue searching. In this paper, we focus on the case where only consideration sets and purchases, but not the sequence of searches are observed and ask the question whether we can say something about the type of search as well.

Hong and Shum (2006) develop methodologies to estimate search costs under both simultaneous and sequential search when only prices are observed. In their model, only price enters a consumer's utility function. Hong and Shum (2006) also make several restrictive assumptions such as companies being identical (and thus consumers randomly picking a company to search), only one distribution of prices in the market, and homogenous products. They find search costs under sequential search to be higher than under simultaneous search. In this paper, we are able to relax several of Hong and Shum's (2006) assumptions: We assume company-specific price distributions, we use a "full" utility specification, and a consumer's decision of which companies to search is guided by the companies' expected and reservation utilities, respectively. Similar to Hong and Shum (2006) we are able to compare search costs under the two assumptions on search strategies.

In a follow-up paper to Hong and Shum (2006), Chen et al. (2007) develop nonparametric likelihood ratio model selection tests based on the Kullback-Leibler Information Criterion (KLIC) to test between models based on a parametric likelihood and moment condition models. In the empirical illustration, the authors apply KLIC test statistics to test between the non-parametric simultaneous search model and the parametric sequential search model presented in Hong and Shum (2006) for two products (Palm Pilot Vx and a statistics textbook by Billingsley). Chen et al. (2007) do not find significant differences between the simultaneous and sequential search models using the usual significance levels. They conclude that this might be due to the small sample sizes (18 price observations for each product) in their empirical illustration.

This paper is also related to Honka (2013). She quantifies search and switching costs for the U.S. auto insurance industry using the same data as we do in this paper. The simultaneous search model presented here is similar to the one Honka (2013) uses.[5] While she assumes that all consumers search simultaneously, we estimate simultaneous, sequential, and mixture models and let the data decide which is the most appropriate specification.

3 Model

We formulate our model to closely mirror the structure of the data that we use for our empirical analysis. There are N consumers indexed by $i = 1, \ldots, N$ who purchase one of J brands indexed by $j = 1, \ldots, J$. Consumer $i's$ indirect utility for company j is given by

$$u_{ij} = \alpha_j + \beta_1 p_{ij} + \beta_2 adv_{ij} + \beta_3 I_{ij,t-1} + Z_{ij}\gamma + \epsilon_{ij} \tag{1}$$

where ϵ_{ij} follows an EV Type I distribution and is observed by the consumer, but not by the researcher. α_j are company-specific brand intercepts; p_{ij} are prices which follow a normal distribution with mean μ_{ij}^p and standard deviation σ_p. Consumers know the distributions of prices in the market, but search to learn the specific price a company is going to charge them. adv_{ij} denotes consumer- and company specific advertising.[6] $I_{ij,t-1}$ is a dummy variable indicating whether consumer i made a purchase from the same company j as in time period $t-1$. Z_{ij} are observed demographic variables. Collectively, $I_{ij,t-1}$ and Z_{ij} account for state-dependence and heterogeneity; if panel data are available we could also account for unobserved heterogeneity. $\alpha_j, \beta_1, \beta_2, \beta_3, \gamma$ are parameters to be estimated. The means of the price distributions are consumer- and company-specific; the standard deviation of prices is not. While it would have been desireable for the latter to be company-specific, we need this assumption to be able to apply the theory developed by Chade and Smith (2005) to estimate the simultaneous search model.[7]

3.1 Simultaneous Search

The simultaneous search model we develop in this section is closely related to the one developed in Honka (2013). The main difference between the two models is that Honka (2013) assumes that prices follow an EV

[5] Note that, in contrast to Honka (2013) who assumes that prices follow an EV Type I distribution, we assume that prices follow a normal distribution. This change is necessary so that we can directly compare the results from the simultaneous and sequential search models.

[6] Advertising is both company *and consumer*-specific as in our empirical application adv_{ij} is an interaction between company-specific advertising spending and consumer- and company-specific advertising recall by a consumer (see Section 7). In most situations the variable will not have the consumer-specific subscript.

[7] We study the effects of the equal price variance assumption in the simultaneous search model when the true price variances are different in a simulation study in Section 6.6.

Type I distribution, while we assume that prices follow a normal distribution as specified in the previous section. This change in distributional assumption is driven by the desire to have the same distributional assumption on prices under both simultaneous and sequential search.[8] Given the normal assumption for prices, the utility u_{ij} is a normally distributed random variable with mean $\mu_{ij} = \alpha_j + \beta_1 \mu_{ij}^p + \beta_2 adv_{ij} + \beta_3 I_{ij,t-1} + Z_{ij}\gamma + \epsilon_{ij}$ and standard deviation $\sigma = \beta_1 \sigma_p$ from the consumer's perspective. A consumer's search decision under simultaneous search depends on the expected indirect utilities (EIU) (Chade and Smith 2005). Consumer $i's$ EIU, where the expectation is taken with respect to price, is given by

$$E\left[u_{ij}\right] = \alpha_j + \beta_1 E\left[p_{ij}\right] + \beta_2 adv_{ij} + \beta_3 I_{ij,t-1} + Z_{ij}\gamma + \epsilon_{ij} \tag{2}$$

Consumer i observes these EIUs for every brand in his market (including ϵ_{ij}). To decide which companies to search, consumer i ranks all companies according to their EIUs (Chade and Smith 2005) and then picks the top k companies to search. The theory developed by Chade and Smith (2005) on the optimality of the ranking according to EIUs only holds under the assumption of first-order stochastic dominance among the price distributions. We implement this requirement by assuming that the variance of the price distributions is identical across companies. We therefore make this assumption for both the simultaneous and sequential search models.[9] Further, we also impose a second restriction on both the simultaneous and sequential search models in order to be able to use Chade and Smith (2005): We assume that search costs are *not* company-specific.[10]

To decide on the number of companies k to obtain prices for, the consumer calculates the net benefit of all possible search sets *given the ranking of EIUs*. A consumer's benefit of a searched *set* S_i is, similarly, given by the expected *maximum* utility among the searched brands. R_{ik} denotes the set of top k companies consumer i ranked highest according to their EIU. For example, R_{i1} contains the company with the highest expected utility for consumer i, R_{i2} contains the companies with the two highest expected utilities for consumer i, etc.

The consumer picks the size of his searched set S_i which maximizes his net benefit of searching denoted by Γ_{ik},[11] i.e. expected maximum utility among the searched companies minus the cost of search

[8]We chose the assumption of normally distributed prices instead of EV Type I distributed prices for both the simultaneous and sequential search model since it allows us to use the approach suggested by Kim et al. (2010) to calculate the reservation utilities under sequential search. Kim et al.'s (2010) estimation approach for the reservation utilities cannot be used when prices follow an EV Type I distribution.

[9]Note that this assumption is not necessary for the sequential search model, but we nevertheless make it to keep everything other than the search method constant across both models. In Section 6.6, we relax this assumption and show in a simulation study that our estimation approach can recover the true parameter values when price variances are company-specific and consumers search sequentially.

[10]Once again, while not necessary for sequential search, we make this assumption to ensure comparability. In Section 6.7, we relax the assumption and show in a simulation study that our estimation approach can recover the true parameter values when search costs are company-specific and consumers search sequentially. We further explore the effects of the identical search cost assumption in the estimation when search costs are truly company-specific under both simultaneous and sequential search.

[11]Note that, in this part of the paper, we use the terms "search" and "consider" and "searched set" and "consideration set"

$$\Gamma_{ik} = E\left[\max_{j\in R_{ik}} u_{ij}\right] - (k-1)\,c \tag{3}$$

As standard in the search literature, we assume that the first search is free to ensure that all consumers search at least once.[12] The consumer picks the number of searches k which maximizes his net benefit of search. If a consumer decides to search k companies, he pays $(k-1)\,c$ as the search cost and will have k companies in his consideration set. Note that given the normal distribution assumption for prices, there is no closed-form solution for the expected maximum utility $E\left[\max_{j\in R_{ik}} u_{ij}\right]$. We will use simulation methods to calculate the expected maximum utility among the searched brands (see Section 4.1).

Once a consumer has formed his consideration set and learned the prices, all price uncertainty is resolved for this set. Both the consumer and the researcher observe prices. The consumer then picks the company with the highest utility among the searched companies, i.e.

$$j = \arg\max_{j\in S_i} u\left(p_{ij}, adv_{ij}, I_{ij,t-1}, Z_{ij}, \epsilon_{ij}; \alpha_j, \beta_1, \beta_2, \beta_3, \gamma\right) \tag{4}$$

where p_{ij} are now the quoted prices for consumer i by company j and S_i is the set of searched brands.

3.2 Sequential Search

Weitzman (1979) showed that it is optimal for a consumer to rank all companies according to their reservation utilities in a decreasing order when deciding on the search sequence (search rule). Reservation utility u^*_{ij} is the utility that makes a consumer indifferent between searching and not searching, i.e.

$$c = \int_{u^*_{ij}}^{\infty} \left(u_{ij} - u^*_{ij}\right) f\left(u_{ij}\right) du_{ij} \tag{5}$$

A consumer stops searching when the maximum utility among the searched companies is larger than the maximum reservation utility among the non-searched companies (stopping rule), i.e.

$$\max_{j\in S_i} u_{ij} > \max_{j'\notin S_i} u^*_{ij'} \tag{6}$$

And finally, the choice rule states that the consumer picks the company with the largest utility among the searched ones

$$j = \arg\max_{j\in S_i} u_{ij} \tag{7}$$

Thus after receiving each quote, the consumer decides to either continue searching or to stop searching and purchase from the set of searched companies. Note that, in contrast to the simultaneous search model, the consideration and purchase stages are not separate.

interchangeably.

[12] Note that we keep this assumption of free first search consistent across both simultaneous and sequential search.

4 Estimation

We start by pointing out the crucial differences between what the consumer observes and what the researcher observes:

1. While the consumer knows the distributions of prices in the market, the researcher does not.
2. While the consumer knows the sequence of searches, the researcher only partially observes the sequence by observing which companies are being searched and which ones are not being searched.
3. In contrast to the consumer, the researcher does not observe ϵ_{ij}.

Since the researcher does not observe the price distributions, these distributions need to be inferred from the data. In other words, the typical assumption of rational expectations (e.g. Mehta et al. 2003, Hong and Shum 2006, Moraga-Gonzalez and Wildenbeest 2008) is that these distributions can be estimated from the prices observed in the data. However, since the parameters of the distribution thus obtained are estimates, the associated sampling error needs to be accounted for when estimating the other parameters of the model (see McFadden 1986).

4.1 Simultaneous Search

To address the second issue, we point out that partially observing the sequence of searches contains information that allows us to estimate the composition of consideration sets. Honka (2013) has shown that the following condition has to hold for any searched set

$$\min_{j \in S_i} \left(E\left[u_{ij} \right] \right) \geq \max_{j' \notin S_i} \left(E\left[u_{ij'} \right] \right) \qquad \cap \qquad \Gamma_{ik} \geq \Gamma_{ik'} \qquad \forall k \neq k' \tag{8}$$

i.e. the minimum EIU among the searched brands is larger than the maximum EIU among the non-searched brands *and* the net benefit of the chosen searched set of size k is larger than the net benefit of any other search set of size k'.

Note that we diverge from the model presented in Honka (2013) in one aspect which is also going to influence our estimation approach for the simultaneous search model. While Honka (2013) assumes that prices follow an EV Type I distribution (and thus the net benefit of a chosen searched set has a closed-form solution), we assume in this paper that prices follow a normal distribution (see also Section 3.1). This change in assumption is driven by the need to have the same assumption on the price distribution for both the simultaneous and sequential search models.[13] This standardization comes at a cost: After imposing the assumption that prices follow a normal distribution the net benefit of a chosen searched set no longer has a

[13] We chose the assumption of normally instead of EV Type I distributed prices as it allows us to use the approach suggested by Kim et al. (2010) to calculate the reservation utilities under sequential search.

closed-form solution. Instead, as we discuss below, we compute Γ_{ik} numerically. We account for the fact that the researcher does not observe ϵ_{ij} (point 3 above) by assuming that ϵ_j has an EV Type I distribution with location parameter 0 and scale parameter 1 and integrate over its distribution to obtain the corresponding probabilities with which we can compute the likelihood function. Then the probability that a consumer picks a consideration set Υ is

$$\Pr\left(S_i = \Upsilon \mid adv_{ij}, \mu^p_{ij}, \sigma_p, I_{ij,t-1}, Z_{ij}; \theta\right) = \Pr\left(\min_{j \in S_i}\left(E\left[u_{ij}\right]\right) \geq \max_{j' \notin S_i}\left(E\left[u_{ij'}\right]\right) \quad \cap \quad \Gamma_{ik} \geq \Gamma_{ik'} \qquad \forall k \neq k'\right) \tag{9}$$

with $\theta = \{\alpha_j, \beta_1, \beta_2\beta_3, \gamma, c\}$. Let us now turn to the purchase decision given consideration. Let J be the base brand for consumer i. Then the consumer's choice probability conditional on his consideration set is

$$\Pr\left(y_i = j \mid adv_{ij}, p_{ij}, I_{ij,t-1}, Z_{ij}, S_i = \Upsilon; \theta\right) = \left(u_{ij} \geq u_{ij'} \quad \forall j \neq j', \quad j, j' \in S_i\right) \tag{10}$$

where y_{ij} is a binary variable indicating whether this brand was chosen and p_{ij} are now the quoted prices. Note that there is a selection issue: Given a consumer's search decision, the ϵ_{ij} do not follow an EV Type I distribution and the conditional choice probabilities do not have a logit form. The consumer's unconditional choice probability is given by

$$\begin{aligned}&\Pr\left(y_i = j \mid adv_{ij}, \mu^p_{ij}, \sigma_p, p_{ij}, I_{ij,t-1}, Z_{ij}, S_i; \theta\right)\\ &\quad = \Pr\left(S_i = \Upsilon \mid adv_{ij}, \mu^p_{ij}, \sigma_p, I_{ij,t-1}, Z_{ij}; \theta\right) \Pr\left(y_i = j \mid adv_{ij}, p_{ij}, I_{ij,t-1}, Z_{ij}, S_i = \Upsilon; \theta\right)\end{aligned} \tag{11}$$

In summary, the researcher estimates the price distributions, only partially observes the utility rankings, and does not observe ϵ_{ij} in the consumer's utility function. Accounting for these differences compared to the consumer, we derived an estimable model with consideration set probability given by (9) and the conditional and unconditional purchase probabilities given by (10) and (11).

We maximize the joint likelihood of consideration set and purchase. The likelihood of our model is given by

$$L = \prod_{i=1}^{N}\prod_{l=1}^{L}\prod_{j=1}^{J} \Pr\left(S_i = \Upsilon \mid adv_{ij}, \mu^p_{ij}, \sigma_p, I_{ij,t-1}, Z_{ij}; \theta\right)^{\vartheta_{il}} \Pr\left(y_i = j \mid adv_{ij}, p_{ij}, I_{ij,t-1}, Z_{ij}, S_i = \Upsilon; \theta\right)^{\delta_{ij}} \tag{12}$$

ϑ_{il} indicates the chosen consideration set and δ_{ij} the company from which insurance is purchased. $\theta = \{\alpha_j, \beta_1, \beta_2, \beta_3, \gamma, c\}$ is the set of parameters to be estimated. Neither the consideration set probability as shown in equation (9) nor the conditional purchase probability as shown in equation (10) have a closed-form solution. Honka (2013) describes how to estimate the simultaneous search model under the assumption of EV Type I distributed prices in four steps in detail. Since our assumption of normally distributed prices results in no closed-form solution for the expected maximum utility among the searched brands, we need to add an additional step to the estimation approach. Therefore the simultaneous search model under the assumption of normally distributed prices is estimated the following way: First, we take Q draws from ϵ_{ij} for each consumer/ company combination. Second (new step), for each ϵ_{ij} draw, we take D (= 200; based on preliminary analyses with different numbers of draws) draws from the price distributions for each consumer/ company combination and calculate the expected maximum utility of a searched set as the average across all D draws.[14] We repeat this step for each ϵ_{ij} draw. Third, for each ϵ_{ij} draw, we calculate the smoothed consideration and conditional purchase probabilities using a multivariate scaled logistic CDF (Gumbel 1961) with tuning parameters $s_1 = ... = s_M = 5$. Fourth, we average the smoothed consideration and conditional purchase probabilities across all ϵ_{ij} draws.

4.2 Sequential Search

To address the second issue under sequential search, we point out that observing a consumer's consideration set allows us to draw two conclusions based on Weitzman's (1979) search rule: First, the minimum reservation utility among the searched companies has to be larger than the maximum reservation utility among the non-searched companies, i.e.

$$\min_{j \in S_i} u^*_{ij} \geq \max_{j' \notin S_i} u^*_{ij'} \tag{13}$$

Otherwise, the consumer would have chosen to search a different set of companies. And second, the stopping and choice rules in equations (6) and (7) can be combined to the following condition

$$\max_{j \in S_i} u_{ij} \geq u_{ij'}, \max_{j'' \notin S_i} u^*_{ij''} \qquad \forall j' \in S_i \setminus \{j\} \tag{14}$$

i.e. the maximum utility among the searched companies is larger than any other utility among the considered companies *and* the maximum reservation utility among the non-considered companies.

Equations (13) and (14) are conditions that have to hold based on Weitzman's (1979) rules for optimal behavior under sequential search and *given the search and purchase outcome* that we observe in the data. At the same time, it must also have been optimal for the consumer not to stop searching and purchase earlier given Weitzman's (1979) rules. The challenge, as specified in the second issue raised at the beginning of this section, is that we do not observe the order in which the consumer collected the price quotes. The critical realization is that, *given the parameter estimates*, the observed behavior must have a high probability of having been optimal.

[14] Note that we hold the set of D draws from the price distributions constant within an estimation as well as across all 50 replications in the Monte Carlo simulations.

To illustrate, suppose a consumer searches three companies. Then the parameter estimates also have to satisfy the conditions under which it would have been optimal for the consumer to continue searching after his first and second search. Formally, in the estimation, given a set of estimates for the unknown parameters, for each consumer i, let us rank all searched companies j according to their reservation utilities $\hat{u}^*_{it}$ (the "^" symbol refers to quantities computed at the current set of estimates) where $t = 1, ..., k$ indicates the rank of a consumer's reservation utility among the searched companies. Note that $t = 1$ ($t = k$) denotes the company with the largest (smallest) reservation utility $\hat{u}^*_{it}$ among the searched companies. Further rank all utilities of searched companies in the same order as the reservation utilities, i.e. $\hat{u}_{i,t=1}$ denotes the *utility* for the company with the highest *reservation* utility $\hat{u}^*_{it=1}$. Then *given the current parameter estimates*, the following conditions have to hold:

If the consumer searched two companies:

$$\hat{u}_{i,t=1} < \hat{u}^*_{i,t=2} \tag{15}$$

In other words, although the *reservation utility* of the company with $t = 1$ is larger than that with $t = 2$ by definition, the *utility* of the company with t=1 is smaller than the *reservation utility* of the company with $t = 2$ thereby prompting the consumer to continue searching. So if the consumer searches three companies:

$$\hat{u}_{i,t=1} < \hat{u}^*_{it=2} \quad \cap \quad \max_{t=1,2} \hat{u}_{it} < \hat{u}^*_{i,t=3} \tag{16}$$

or generally if the consumer searches $t = 2, \ldots, k$ companies

$$\bigcap_{l=2}^{k} \max_{t<l} \hat{u}_{it} < \hat{u}^*_{it=l} \tag{17}$$

To calculate a consumer's reservation utilities, we follow the approach suggested by Kim et al. (2010, page 1011). The additional estimation conditions as described in equation (17) are necessary to correctly recover search costs. These conditions impose restrictions on the utilities and bound the parameters more tightly. Without these conditions, search cost estimates are biased upwards. We describe the reason for this bias in the Identification section (section 5.3).

Since in the sequential search model, in contrast to the simultaneous search model, there are no separate consideration and conditional purchase stages, the probability of observing a consumer search a set of companies Υ and purchase from company j under sequential search is

$\Pr\left(S_i = \Upsilon \cap y_i = j \,|\, adv_{ij}, \mu^p_{ij}, \sigma_p, p_{ij}, I_{ij,t-1}, Z_{ij}, S_i; \theta\right)$

$$= \Pr\big(\min_{j \in S_i} u^*_{ij} \geq \max_{j' \notin S_i} u^*_{ij'} \quad \cap \quad \max_{j \in S_i} u_{ij} \geq u_{ij''}, \max_{j' \notin S_i} u^*_{ij'} \quad \cap$$

$$\bigcap_{l=2}^{k} \max_{t<l} \hat{u}_{it} \ < \ \hat{u}^{*}_{it=l} \qquad \forall j'' \in S_i \setminus \{j\}\,,\ t = 2, \ldots, k \quad) \tag{18}$$

Then the loglikelihood of the model is given by

$$L = \prod_{i=1}^{N} \prod_{l=1}^{L} \prod_{j=1}^{J} \Pr\left(S_i = \Upsilon \cap y_i = j \,|\, adv_{ij}, \mu^{p}_{ij}, \sigma_p, p_{ij}, I_{ij,t-1}, Z_{ij}, S_i; \theta\right)^{\vartheta_{il}} \tag{19}$$

ϑ_{il} indicates the chosen consideration set and the purchased company.

In principle, we can write out all rankings of utilities and reservation utilities that satisfy the conditions in equation (18) and write the probability of observing a consumer's search and purchase behavior by calculating the sum of the probabilities of all admissable rankings. The challenge with writing out all utility and reservation utility rankings that satisfy the conditions in equation (18) is that their number and complexity increases very quickly with the number of searches a consumer makes. Since, in our empirical application, we observe consumers searching up to ten times in our data, this approach is not feasible. A second challenge is that, even if we wrote out all admissable rankings of utilities and reservation utilities, the probability as described in equation (18) does not have a closed-form solution. We use SMLE to estimate the sequential search model as it allows us to overcome both challenges. SMLE does not solve the combinatorial problem, but it circumvents it by allowing us to estimate the probability of observing a consumer search a set of companies Υ and purchase from company j in equation (18) without having to write out all admissable rankings.

As in the estimation of the parameters in the simultaneous search model, we use a kernel-smoothed frequency simulator (McFadden, 1989) and smooth the probabilities using a multivariate scaled logistic CDF (Gumbel, 1961). We describe the details of our estimation approach in Appendix A.

5 Identification

We first discuss how the search method is identified with our data. Next, we describe the identification of the model parameters conditional on an assumed search method. Our discussion of identification rests on the assumption consumers know the distribution of prices. As is common in the search literature, we assume that consumers have rational expectations for prices and that the researcher can estimate these price distributions from prices observed in the marketplace.

5.1 Search Method

We start out by discussing the data pattern that is identifying simultaneous search. Recall that prices follow company-specific distributions, i.e. $p_j \sim D_j(\mu_j, \sigma_j)$. Let us define $\Pr(p_j \leq \mu_j) = \lambda$, i.e. the probability that a price draw is below the distribution mean is λ. If we define event $X = 1$ as a below-mean price draw and $X = 0$ as an above-mean price draw.Recall that under simultaneous search the search rule says that the consumer pre-commits to a search set S_i consisting of k_i companies. Then we can calculate the expected proportion of below-mean price prices in a consumer's consideration set of size k as

$$E\left[\frac{1}{k}\sum_{m=1}^{k} X_m\right] = \frac{1}{k}\sum_{m=1}^{k} E[X_m] = \frac{\lambda k}{k} = \lambda$$

Thus, under simultaneous search, we expect $\lambda\%$ of the price draws in consumers' consideration sets to be above above and $(1-\lambda)\%$ above the mean prices. The crucial ingredients for identification are that the researcher observes the means of the price distributions μ_j, the actual prices in consumers' consideration sets p_j and the probability of a price draw being below its mean λ.

Since we assume in the empirical sections of this paper that prices follow normal distributions, the probability that a price draw is below its mean or, equivalently, of event X is $\frac{1}{2}$. Then the expected proportion of below-mean price price draws in a consideration set of size k is $\frac{1}{2}$, i.e. we expect 50% of the price draws to be below and 50% of the price draws to be above the price means.

This data pattern for prices in consideration sets under simultaneous search can be expected for (1) models with homogeneous goods, (2) models with differentiated products, (3) models that include unobserved heterogeneity in preferences and/ or search costs, (4) models with correlated price distributions and (5) models with correlations among preferences, search costs and price distributions. The reason why identification goes through in all these settings is that in all five situations, the determination of which and how many companies to search is based on the net benefit of searching Γ_{ik}. .. For the search method identification, this decision is taken as given, i.e. given that the consumer has decided to search a specific set of companies, we look at the resulting price patterns. Further, our identification strategy also holds for models with observed heterogeneity in price distribution means μ_{ij} as the researcher can still judge whether a price is below or above its mean. On the other hand, our identification strategy does no longer hold when there is *un*observed heterogeneity in the price distribution means (across consumers) as the researcher would no longer be able to judge whether a price draw is above or below its mean. Our identification strategy also does not hold when consumers get new information about price distributions from observing other variables (e.g. advertising). The intuition behind this result is that the condition $\Pr(p_j \leq \mu_j) = \lambda$ is violated in this case. While, if both the researcher and the consumer observed the other variable (e.g. advertising), we could condition the price distribution on this observation, λ would no longer be the same across all companies and our identification strategy no longer works.

We now turn to sequential search and the data pattern that identifies this search method. We start out by giving the intuition for identification for the homogeneous goods case and show the analytical results for both the homogeneous and differentiated goods cases in Appendix B.

In the homogeneous goods case, consumers search to find the lowest price, i.e. $u_{ij} = p_{ij}$; have the same search cost c and the same reservation price p^*. Prices follow a market-wide distribution, i.e. $p \sim D(\mu; \sigma)$. Then ***if*** the reservation price p^* were observed by the researcher, the proportion of below-p^* prices in consumers' consideration sets would always equal $\frac{1}{k}$. The intuition for this result is the following: The search rule under sequential search says that the consumer stops searching ***when and only when*** he gets a price draw below his reservation price p^*. Thus if the researcher observes a consumer making k searches, there must at least be one below-p^* price draw in the consumer's consideration sets - otherwise the consumer would have never stopped searching. And there cannot be more than one below-p^* price draw in the consumer's consideration sets as the search rule says that the consumer stops searching when he gets the first price draw below his reservation price p^*. Now, the researcher usually does not observe a consumer's reservation price p^*, but can observe the expected price μ. The reason that the declining pattern of below-mean price prices in consumers' consideration sets goes through is that a below-mean price price draws is always more likely to also be below the consumer's reservation price than an above-mean price price.

In Appendix B, we show analytically that this identifying pattern always holds for both homogeneous and differentiated goods. We also find this identifying data pattern in models with unobserved heterogeneity in preferences and/ or search costs, in models where preferences and search costs are correlated and in models where there is observed heterogeneity in price distribution means μ_{ij}. Similar to simultaneous search, our identification strategy does not work when there is unobserved heterogeneity in price distribution means (across consumers) and when observing another variable (e.g. advertising) gives the consumer new information about price distributions.[15]

For the homogeneous goods case, there is a second data pattern that helps identifying sequential search, namely, that the proportion of consumers searching k times decreases as k increases.[16] Suppose there are N consumers. Then the proportion of consumers searching k times is $\frac{\Pr(s=k)N}{N} = (1-q)^{k-1} q$ and it is easy to show that this proportion decreases as k increases. We refer the reader to Appendix B for detailed results.

[15]We are currently working on assessing whether identification goes through for the sequential search model with correlated price distributions.

[16]Under simultaneous search, the distribution of the number of searches across consumers can either have an inverse U-shaped pattern or decline as well.

5.2 Simultaneous Search Model

We provide a brief summary of the discussion of identification of the model parameters under simultaneous search and refer the reader to Honka (2013) for more details. The identification of the parameters capturing differences in brand intercepts, the effects of advertising and price and demographic effects that vary across companies is standard as in a conditional choice model. These parameters also play a role in consumers' consideration set decisions.

The size of a consumer's consideration set will help pin down search costs. We can only identify a range of search costs as it is utility-maximizing for all consumers with search costs in that range to search a specific number of times. Beyond the fact that a consumer's search cost lies within a range which rationalizes searching a specific number of times, the variation in our data does not identify a point estimate for search costs. The search cost point estimate will be identified by the functional form of the utility function and the distributional assumption on the unobserved part of the utility.

Recall that we assume that the first search is free. The base brand intercept is identified from the consumer's decision to search or not to search beyond the free first search. Intuitively speaking, the free first search assumption creates a "fall-back option" similar to the outside option and allows us to identify the base brand intercept. So while the search cost estimate is pinned down by the average number of searches, the base brand intercept is identified by the search or no search decision (beyond the free first search).

Demographic effects that do not vary aross companies are identified by consumers with certain characteristics searching more or less than others. For example, suppose consumers who dread the insurance shopping and purchase process as measured by the psychographic factor "Attitude towards auto insurance shopping and switching" search less than consumers who enjoy this process. Then - given that the search cost coefficient is identified by the average number of search across all consumers - consumers who dislike shopping for auto insurance must have a smaller benefit of searching, i.e. a lower utility for insurance, than consumers who like this activity. Thus we would expect a negative coefficient for this psychographic factor in the utility function. It is important to recognize that this argument only holds under the assumption of identical search costs across consumers. Alternatively, we could allow the demographic variables to shift the search costs but not the utility functions.

5.3 Sequential Search Model

In the sequential search model, the parameters capturing differences in brand intercepts, the effects of advertising and price and demographic effects that vary across companies are identified from the conditions on the utilities and reservation utilities, i.e. equations (13), (14) and (17). Search costs are identified from

Weitzman's stopping rule (equation 6 or 14). They are not identified from the search rule as it only imposes a *relative* ranking on the reservation utilities. Recall that the reservation utility is the utility that makes a consumer indifferent between searching and not searching (equation 5). If there is a unique solution for equation 5 as has been shown by previous research (e.g. Kim et al. 2010) and search costs are not company-specific as we assume in our model, then the *relative* ranking of the reservation utilities will not change when search costs equally increase or decrease for all companies. Thus search costs are not identified from Weitzman's search rule. Search costs are also not identified from Weitzman's choice rule (equation 7) as search costs do not enter it. Search costs are identified by the stopping rule only as it looks at the relationship between utilities and reservation utilities.

Previous research (e.g. Kim et al. 2010) has shown that as search costs increase, reservation utilities decrease. Thus, as search costs increase, the stopping rule demanding that the maximum utility among the searched companies is larger than the maximum reservation utility among the non-searched companies is satisfied earlier and consumers stop searching earlier. This is the mechanism behind the intuitive result that higher search costs make consumers search less. The number of searches a consumer makes identifies a range of search costs as it is utility-maximizing for a consumer with search costs in that range to search a specific number of times. For example, suppose it is optimal for a consumer to search once if his search costs lie between two and three, twice if his search costs lie between one and two and three times if his search costs lie between zero and one. Then by observing the consumer stop after the second search, we know that his search cost must be at least one, but we do not know whether his search costs are one, two or three. Thus imposing the stopping rule as shown in equation 5 on the observed consideration set only puts a lower bound on the search cost estimate as it only requires that search costs must have been larger than a lower bound to make the consumer stop searching. As a consequence, if only the stopping rule on the *observed* consideration set is used in the estimation, the search cost estimate exhibits an upward bias. This is the upward bias on the search cost estimate we described in Section 4.2. By imposing the conditions that, given the current estimates, it must have been optimal for the consumer to continue searching (equation 17), we impose an upper bound on the search cost estimate which eliminates the previously described upward bias of the search cost estimate and allows us to recover the true values. The intuition here is that if the search costs had been higher, the consumer would not have continued searching. Beyond the fact that a consumer's search cost lies within this range which rationalizes stopping after a specific number of searches (but not earlier), the variation in our data does not identify a point estimate for search costs. The search cost point estimate will be identified by the functional form of the utility function and the distributional assumption on the unobserved part of the utility (as in the case of the simultaneous search model).

The base brand intercept - as in the simultaneous search model - is identified by a consumer's decision to search or not to search more than once given our assumption that the first search is free. Thus observing a proportion of consumers to only search once (and "pay" no search costs) is crucial in identifying the base brand intercept. Note that, in contrast to the simultaneous search model, demographic effects that do not vary across companies are not identified in the sequential search model. These demographic effects are not identified from the choice or search rules as adding a constant to all utilities or reservation utilities does not change the relative rankings among the utilities or reservation utilities, respectively. These demographic effects are also not identified from the stopping rule as adding a constant to the utility function does not affect the relationship between utilities and reservation utilities, i.e. whether a specific utility or a specific reservation utility is larger. The intuition behind this result is the following: Based on Kim et al. (2010), we know that a reservation utility in our model can be calculated as the sum of expected utility (expectation taken with respect to price) and a constant that depends on search costs, the price coefficient and the standard deviation of the price distribution. Thus, for the same company j, any difference in utility for company j and reservation utility for company j comes from the difference in expected and actual price. For different companies, any difference in utility for company j and reservation utility for company j' comes from the difference in actual price for company j and expected price for company j' and differences in company-specific observed variables. Thus demographic effects that do not vary across companies do not affect the relationship between utilities and reservation utilities and are not identified from the stopping rule.

The lack of identification of the effects of demographic characteristics that do not vary by alternative on the utility function in the sequential search method raises the issue of how to introduce demographic characteristics in models of search. For the simultaneous search model, these variables can be introduced either directly in the utility function or as shifters of search costs across consumers. For the sequential search model, only the latter operationalization is feasible. In the empirical application we explore the consequences of introducing demographics - either in the utility function or in the search cost.

6 Monte Carlo Simulations

We present two sets of simulation results. In the first set, we assess whether knowledge of the price distributions, consideration sets and actual prices realized for the alternatives in the consideration set allow us to say something about the nature of the search strategy being employed by consumers. This is for the simple case where consumers' utility functions are given as: $u = -p$. Next we extend this to the situation where consumers have a fully specified utility function, i.e. $u_{ij} = \alpha_j + \beta p_j + X_{ij}\gamma + \epsilon_{ij}$. These simulations address the issue of identification of the search method.

Our objectives for the second set of simulation studies are the following. First, as a check, we would like to ensure that our estimation algorithms are able to recover the parameters corresponding to the true data generating process (DGP). Next, we want to understand the consequences (estimates, fit etc.) of assuming an incorrect search strategy when estimating the model parameters - to this end we generate data under a simultaneous (sequential) search strategy and estimate the model parameters under a sequential (simultaneous) approach. Finally, we use the simulation studies to understand the consequences of two assumptions that our simultaneous search model makes - the equal variance assumption for the price distributions of the alternatives and the assumption of identical search costs for the different alternatives. In the former case, we generate data using the two strategies but with each firm having its own variance for the price distributions. Then we estimate the parameters under the two strategies after imposing the equal variance assumption. Since our sequential estimation approach can accommodate different variances, we estimate that model when the data are generated under the same assumption to ensure that our estimation approach is appropriate in the unequal variance case. To study the equal search cost assumption, we generate data under the unequal search cost assumption and then estimate the correct model but imposing the restriction of equal search costs.

6.1 Generated Data

In all simulation studies, we generated data for 1,000 consumers (to mimic the size of the sample in our data). For the the homogenous goods case in the first set of simulation studies, we use the utility function $u = -p$ and search costs of .6. Prices follow a normal distribution with a mean of 3 and a standard deviation of .5. Data are generated under both search methods - simultaneous and sequential.

For the differentiated goods case in the first and second set of simulation studies, we use a simplified version of our main model for the Monte Carlo simulations. Consumer i receives utility for company j in the following form

$$u_{ij} = \alpha_j + \beta_1 p_{ij} + \beta_2 adv_{ij} + \epsilon_{ij}$$

We simulate data under the following two assumptions: (1) all consumers search simultaneously and (2) all consumers search sequentially. We generate the data using the following three steps: First, we fix all parameters to their true values,generate the independent variables (consumer- and company-specific prices and advertising) and draws from the error distribution for all 1,000 consumers. We provide more details on the indepedent variables in the next paragraph. Second, for the case when all consumers search simultaneously only, we generate 100 draws from the price distributions (for each consumer/ company combination) to numerically approximate the expected maximum utility among the search companies (see equation (3)) which does not have a closed-form solution. And finally, using the true parameter values, the generated independent variables and error draws, we calculate the optimal behavior for each consumer, i.e. the optimal number of searches, the companies to search and the company to purchase from.

The independent variables were generated to largely mimic the characteristics of the data in our empirical application with the difference being that we focus on a smaller set of six brands. As mentioned in the previous paragraph, the independent variables are price and advertising. We pick the true values of the six brand intercepts (-2.0, -1.6, -2.1, -2.4, -1.4, -1.8) to be similar to the brand intercepts of the six largest insurance companies in our empirical application. Prices in our simulation studies are normally distributed with mean prices of .45, .55, .10, .07, -.10, .43 and a standard deviation of 2.00. The choice of mean prices and the standard deviation is again driven by the empirical application. After regressing prices (measured in $100) on a large set of consumer characteristics (see left column in Table 11 plus the chosen coverage, state and make/ class dummies), we find the company-specific price residuals to have means and a standard deviation similar to the one we use in these simulation studies. This implies that even after accounting for consumer characteristics, large price differences across insurance companies remain.

The distributions of the advertising data are company-specific with mean advertising levels of 2.7, 4.6, 3.0, 1.9, .5, .6 and standard deviations of 1.2, .75, .25, .65, .2, .5, respectively. The means and standard deviations of the simulated advertising data were chosen to be similar to the advertising spending levels we observe in the auto insurance data. Note that the advertising spending data was scaled by $10,000,000, i.e. 2.7 reflects a monthly advertising spending level of $27,000,000. When simulating advertising data for consumers, we take consumer-specific draws from the company-specific advertising distributions. We generate this advertising data that is both consumer- and company-specific to mimic the advertising data in our empirical application. There, advertising is also consumer- and company-specific measured through an interaction effect of company-specific advertising spending and consumer-specific advertising recall. We assume that the first search is free to ensure that all consumers participate in the market. The true search cost for all consumers is .3 in terms of utility. We chose the true price coefficient to equal -1.0 so that search costs in terms of dollars are $30 - a similar magnitude to the one found by Honka (2013) for auto insurance. The advertising coefficient was set to .5 in the simulations.

In the estimations, we run 50 replications of each experiment described above, each time using a different set of draws from the error distribution ϵ_{ij}. The reported parameter estimates are the means and standard deviations of the parameter estimates across these 50 replications.

6.2 Search Method

We start by showing the different data patterns in actual prices in consumers' consideration sets generated by the two search methods. The upper half of Table 1 shows the results for the homogenous goods case with $u_{ij} = -p_{ij}$. As expected based on our discussion in the Identification section 5.1, under simultaneous search, the percentage of below-average actual prices in a consumer's consideration set is about 50% across all consideration set sizes and all consumers. By contrast, under sequential search the percentage of below-average actual prices in a consumer's consideration set is decreasing with the increase in the size of the consideration set.

The lower half of Table 1 shows the results for the differentiated goods case with $u_{ij} = \alpha_j + \beta_1 p_{ij} + \beta_2 adv_{ij} + \epsilon_{ij}$. We find similar patterns to the homogenous goods case. Under simultaneous search, the percentage of below-average actual prices in a consumer's consideration set is about 50% across all consideration set sizes and all consumers and under sequential search, the percentage of below-average actual prices in a consumer's consideration set is decreasing as consideration sets increase in size. The patterns in these simulation studies confirm the results of the Identification section.

6.3 Data Patterns

Next, we characterize the different data patterns (beyond those described in the previous section) that arise as a consequence of different search types. We first compare aggregate patterns and then move on to compare patterns at a more granular lever. 64.50% of consumers search a different number of times across the two search modes. The average number of searches is 2.27 under simultaneous and 1.94 under sequential search. This represents a decrease of 14.5% in the average number of searches. Graph 1 shows a histogram of the distributions of searches. Note that the distribution of the number of searches has a longer tail under sequential than under simultaneous search.[17] While at the individual level, a consumer might search the same, more or fewer companies when switching from simultaneous to sequential search, we find that 35.5% of consumers search the same number of companies and 47.2% (17.3%) of consumers search fewer (more) companies under sequential versus simultaneous search.

Table 2 shows the percentages of consumers that consider a brand. Since consumers search on average fewer companies under sequential versus simultaneous search, the percentages in column B are lower than in column A. Recall that the average number of searches drops by 14.5% when consumers switch from simultaneous to sequential search. Similarly, the percentages of consumers considering brands 1 through 4 also decrease by about 15%, while the drop is much smaller for brand 5 (-11%) and much larger for brand 6

[17] The maximum number of searches under simultaneous and sequential search is 4 and 6, respectively.

(-19%).

Table 3 displays the purchase market shares and conversion rates. At the aggregate, the purchase market shares are relatively similar. Columns C and D show the conversion rates under simultaneous and sequential search, respectively, and column E shows the change in conversion rate when going from simultaneous to sequential search. The conversion rates captures the probability that a consumer who considered a brand is going to purchase from this brand. On average, the conversion rates under sequential search are higher than under simultaneous search. This is driven by consumers searching fewer companies under sequential search, while they still purchase the same amount, i.e. each consumer makes one purchase. Brands 3 and 6 show the highest and brands 2 and 5 the lowest increase in conversion rates when going from simultaneous to sequential search.

Even though a change in search method does not affect the aggregate purchase market shares, it is important to note that it has a large effect on the data at a more disaggragate level. First, 15.70% of consumers change the company they purchase from solely as a consequence of the type of search they use (since all the parameters and all generated data are held fixed). Among consumers who consider different sets of companies,[18] 24.3% purchase from different companies, while the remainder purchases from the same company under both search methods. And second, the search method has a large effect on company's customer bases. The upper half of Table 4 shows the percentage of customers that change in a company's customer base (using the customer base under simultaneous search as baseline) when consumers change the way they search. This change is coming from customers either no longer buying from a brand or newly buying from a brand.[19] From a company's perspective, a change in search method has dramatic consequences on its customer base. For the six companies in our data, between 25.3% and 58.7% of their customer base changes. In general, the larger a company's market share, the smaller the effect of a change in search method on its customer base is. The lower part of Table 4 displays the average number of searches customers of a brand make. It can be thought of as a measure of competition: The more companies are in a consumer's consideration set, the stronger the competition is. Since consumers search fewer companies under sequential search, the average consideration set size under this search method is smaller compared to simultaneous search. But there is a large variation in the amount of reduction of the consideration set size across companies. For example, customers of company 2 search 25.1% fewer companies, while customers of company 6 search only 6.1% fewer companies under sequential versus simultaneous search.

To summarize, keeping all utility parameters, independent variables and error terms the same, the type

[18] Consumers who consider the same set of companies under both search methods always purchase from the same utility-maximizing company (see equation 4 for the simultaneous and equation 7 for the sequential search model).

[19] Since every consumer who is switching companies was buying before and is buying after the switch, every consumer is counted twice (once for leaving a company and once for being a new customer to a different company).

of search alone has a significant influence on the resulting data patterns in terms of which and how many companies consumers search and which company consumers purchase from.

6.4 Type of Search Known

Table 5 shows the estimation results when the true data generating process is known to the researcher. Column (A) shows the results when all consumers search simultaneously and column (B) when all consumers search sequentially.

Generally, our estimation approaches are able to recover consumer preferences and search costs well under the assumption of the true DGP. In the estimation we also tried a variety of starting values to assess the sensitivity of our results to starting far away from the true values. We find that starting with values that are e.g., all zero or are several times the true values does not result in different sets of converged values.

6.5 Type of Search Unknown

In most empirical settings, the type of search consumers use is unknown to the researcher and the researcher makes an assumption on the type of search consumers use. Table 6 investigates what happens when the wrong type of search is assumed. In column (A), the true type of search is simultaneous, but the researcher assumes sequential search, while in column (B) the true type of search is sequential, but the researcher assumes consumers search simultaneously in the estimation. In both cases, true consumer preferences are no longer recovered (especially the price coefficient) and the search cost estimates are very close to zero. Comparing the loglikelihoods from column (A) (Table 5) and column (A) (Table 6), the loglikelihood is worse on average across all 50 replications as well *as for every individual replication* when the wrong type of search is assumed. A similar picture emerges by comparing the loglikelihoods from column (B) (Table 5) and column (B) (Table 6). These results indicate that imposing the wrong type of search when estimating the model's parameters leads to a model fit that is worse than that corresponding to the correct model across all replications. We take this as evidence that the fit statistic is able to correctly lead us to the true type of search conditional on our model structure. Based on our earlier discussion of the identification of the search method, one can see why the model fit deteriorates under the incorrect search assumption. In essence, when fitting the simultaneous search assumption, the model is looking for prices in the consideration set that fall above and below the mean price distribution equally. However, if the data are generated from the sequential search model, prices do not conform to this pattern; not only do the parameters deviate from those under simultaneous search in such a situation, the model simply cannot do a good job explaining the patterns in the data.

Next, we take a closer look at the search cost estimate from Table 6. Theoretically, we expect search costs to be biased downwards, i.e. smaller than their true value, if the true DGP is simultaneous search, but a sequential search model is estimated. This prediction is confirmed in column (A) (Table 6) where we find a search cost estimate of .02, while the true search costs parameter is .30. Similarly, we expect search costs to be biased upwards, i.e. larger than the true value, when the true data generating process is sequential search, but a simultaneous search model is estimated. This prediction is *not* confirmed in column (B) (Table 6) where we find a search cost estimate of .00. The reason for this result lies in the fact that the corresponding theoretical prediction only holds for the case where $u = -p$. Once we move to a full utility specification as in our model, it no longer holds. To illustrate this point, we fix all parameters to their true values and ONLY estimate the search cost parameter under the wrong type of search assumption. Table 7 displays the results. We now find the expected pattern where search costs are biased downwards under the wrong assumption of sequential search (column A) and biased upwards under the wrong assumption of simultaneous search (column B).

6.6 Unequal Variances in Price Distributions

In our main model in Section 3, we assume that the variances of the price distributions are constant across companies. This assumption is necessary for the simultaneous search model to be able to apply the theory developed by Chade and Smith (2005). This assumption is not necessary for the sequential search model, but we nevertheless apply it to keep everything constant across the two search methods. In this section, we explore two issues related to the equal variance assumption: First, we show that we can relax this assumption, i.e. assume company-specific price variances, in the sequential search model and our estimation method is still able to recover the true values. And second, we study the consequences of the equal variance assumption on the estimates when the data are generated with company-specific price variances under both simultaneous and sequential search.

To study the effects of the equal variance assumption, we generate two new sets of data. In the first set of data, all consumers search simultaneously; in the second data set, all consumers search sequentially. The only difference to the data sets we described at the beginning of Section 6 is that instead of assuming that the variance of the price distributions is constant across companies and equals $2^2 = 4$, we assume that the standard deviations of the company-specific price distributions are 1.0, 1.5, 2.0, 2.0, 2.5, 3.0. Note that the price variance across all companies remains 4. Also note that to generate the data under simultaneous search, we can no longer rely on the ranking according to the expected indirected utilities. Instead, we simulated all possible consideration sets varying by their size and composition and let the consumer choose the one with the highest benefit net of search costs.

Column (A) in Table 8 shows that, in a sequential search model, we can recover the true parameter values when the data are generated with company-specific price variances and we assume this as well in the estimation. Columns (B) and (C) explore the effects of the equal variance assumption on the estimates when the data was generated with company-specific price variances under both simultaneous and sequential search, respectively. In general, true consumer preferences cannot be recovered in these cases. Under simultaneous search (column (B)), we find the search cost estimate to be severely downward biased. The search cost estimate is .01 (std. err. .00), while the true search cost parameter is .30. This also holds for search costs in dollars where the true value is \$30, while the estimated search costs are \$4. Under sequential search (column (C)), the search cost estimate and the estimates for price and advertising effects also show a downward bias. The search cost estimate is .13 (std. err. .05), while the true search cost parameter is .30. This also holds for search costs in dollars where the true value is \$30, while the estimated search costs are \$20.63. At the same time, the model does a reasonable job of recovering the preferences. Further and similar to our simulation study results with an unknown search type, the loglikelihood for the sequential search model is worse across all 50 replications as well *as for every individual replication* when the wrong assumption of equal price variances is made. The bottom line on our results here is that it is critical that the equal variance assumption holds in the data, especially for the simultaneous search model, for us to have some reassurance regarding our results. In our empirical application, we estimate the sequential search model under both equal and unequal variance assumptions to assess their implications.

6.7 Identical Search Costs Across Companies

In our main model in Section 3, we assume that search costs are identical across companies. This assumption is necessary for the simultaneous search model to be able to apply the theory developed by Chade and Smith (2005). This assumption is not necessary for the sequential search model, but we nevertheless apply it to keep everything constant across the two search methods. In this section, we explore two issues related to the identical search cost assumption: First, we show that we can relax this assumption, i.e. allow for company-specific search costs, in the sequential search model and our estimation method is still able to recover the true values. And second, we study the consequences of the identical search cost assumption on the estimates when the data was generated with company-specific search costs under both simultaneous and sequential search.

To study the effects of the identical search cost assumption, we generated two new sets of data. In the first data set, all consumers search simultaneously; in the second data set, all consumers search sequentially.

The only difference to the data sets we described at the beginning of Section 6 is that instead of assuming that search costs are constant across companies and equal .3, we assume that the company-specific search costs are .3, .2, .1, .4, .5, .3. Note that the average search costs across all companies remain .3; the average *actual* search costs that consumers incur in the data we generate are .23. Note that to generate the data under simultaneous search, we could no longer rely on the ranking according to the expected indirected utilities. Instead, we simulated all possible consideration sets varying by their size and composition and let the consumer choose the one with the highest benefit net of search costs.

Column (A) in Table 9 shows that, in a sequential search model, we can recover the true parameter values when the data was generated with company-specific search costs and we assume this as well in the estimation. Columns (B) and (C) explore the effects of the identical search cost assumption on the estimates when the data was generated with company-specific search costs under both simultaneous and sequential search, respectively. Under simultaneous search (column (B)), consumer preferences are incorrectly estimated. The search cost estimate exhibits a severe downward bias. While the true search cost coefficient is .3, the estimated search cost coefficient is .03 (std. err. .00). This also holds for search costs in dollars where the true value is \$30, while the estimated search costs are \$7.50. Under sequential search (column (C)), the search cost estimate and the effects of price and advertising exhibit a downward bias, although not as severe as when the incorrect search method is assumed or even when compared to the unequal variances case above. The estimated search cost coefficient is .15 (std. err. .04) or, in terms of dollars, \$20.27. Recall that the true values are .30 and \$30. Further, and similar to our simulation study results with an unknown search type, the fit of the sequential search model is worse across all 50 replications as well *as for every individual replication* when the wrong assumption of equal search costs is made. Note that in this case we cannot use the log-likelihood as a basis for comparison since the number of estimated parameters differs across models so instead we use the Bayesian Information Criterion (BIC) that penalizes the estimation of additional parameters (see e.g., XX). Our results here indicate that it is important that the assumption of identical search costs holds in the data, especially for the simultaneous search model, for us to have some reassurance regarding our results. In our empirical application, we estimate the sequential search model under both equal and unequal search cost assumptions to assess their implications.[20]

Overall, our findings from the simulation studies are as follows: First, looking at the patterns in prices in the observed consideration sets is informative of the search method being used by consumers. Next, our estimation approaches are able to recover consumer preferences and search costs well under the assumptions of the true DGP. When the wrong assumptions, e.g. on search type, equal price variances or equal search

[20]The results of the sequential search model with unequal search costs are currently not available and will be added to the next version of this paper.

costs, are imposed in the estimation, true consumer preferences and search costs are no longer recovered. But, more importantly, when the model is estimated under both alternative assumptions, e.g. simultaneous and sequential search or equal and unequal price variances, the loglikelihood is able to predict the true assumption on average and in every single replication.

7 Empirical Application

We use data on consumer search and purchase behavior for auto insurance from an insurance shopping study conducted in 2006 and 2007 by a large market research company. We observe which companies consumers got price quotes from and which they signed up with. This gives us information on the number and identity of companies searched and the purchase decision. In addition, we observe monthly company-specific advertising spending, consumer- and company-specific advertising recall and quoted prices. We also have data on demographic variables, psychographic factors and observed consumer attitudes towards insurance companies. Table 10 contains descriptive statistics of our data. We refer the reader to Honka (2013) for a detailed description of our data.

Before receiving a specific price quote, we assume consumers have rational expectations about prices. We estimate consumers' price expectations using prices charged by previous insurers and a large set of variables that determine insurance prices such as demographics, drivers, cars, location, past claims history, other insurance products and coverage choices. We assume that prices follow a normal distribution with the mean being a function of the variables that determine insurance prices and a constant variance. Note that this assumption reflects a departure from Honka (2013): While she assumes that prices follow an EV Type I distribution, we assume that they follow a normal distribution. The estimation results are shown in Table 11. We use the predicted prices from this regression as price expectations in the main model estimation. Note that within a consumer, the expected prices across firms only vary due to the company-specific fixed effects. We refer the reader to Honka (2013) for details on the price expectation estimation process.

7.1 Utilty Function

To describe consumer's utility for auto insurance, we use the utility function described in equation 1, i.e.

$$u_{ij} = \alpha_j + \beta_1 p_{ij} + \beta_2 adv_{ij} + \beta_3 I_{ij,t-1} + Z_{ij}\gamma + \epsilon_{ij} \tag{20}$$

with

$$adv_{ij} = adspending_j * adrecall_{ij}$$

With an average retention rate of about 70% in the auto insurance industry, capturing consumer inertia through β_3 is necessary to fully describe consumer behavior in this market. Further, we also control for the following four demographic variables denoted by Z_{ij} in the utility function: attitude towards auto insurance shopping and switching, new technology adoption, proven reliability and out-of-box character. While the first two variables are consumer-specific, the last two variables (proven reliability and out-of-box character) are both consumer- and company-specific. Attitude towards auto insurance shopping and switching and new technology adoption are psychographic factors that we retrieved from the data using factor analysis. Proven reliability and out-of-box character describe consumer's attitudes towards each considered insurance company. We also recovered these two factors using factor analysis from the survey data. We provide summary statistics of the items that constitute the four demographic factors in Appendix C. We chose to include these four factors as Honka (2013) has shown that they are significant in a consumer's utility function for auto insurance. Recall that, under sequential search, the effects of consumer-specific variables in the utility function cannot be identified (see discussion in Section 5.3). We will therefore also explore the effects of these variables on search costs by making these costs a function of the demographics.

It is common practice in the auto insurance industry that consumers receive a renewal offer about one month before their policy is set to expire. We view this renewal offer as a "free" first search since the consumer does not have to exert any effort to receive the price quote. Further, we assume that the consumer knows the price his previous insurer is going to charge him to renew his insurance policy before making the decision (not) to search other companies. Finally, we assume the search set S_i contains all companies the consumer actively searches and the consumer's consideration set C_i contains all searched companies and the previous insurer, i.e. $C_i = S_i \cup \{j_{I_{ij,t-1}}\}$.

7.2 Model-free Evidence of Search Method

We explore the data for evidence of the search method consumers' use in two ways: First, we show the patterns of below and above expectation prices in consumers' consideration sets and, second, we use an adapted version of a search method test suggested by De los Santos et al. (2012).

Table 12 displays the average proportion of below-expectation prices in consumers' consideration sets in the insurance data. Recall that under simultaneous search, we expect the proportion to be around 50% across all consideration set sizes and all consumers, while under sequential search, we expect the proportion to decrease as consideration sets increase in size. The average proportions of below-expectation prices in consumers' consideration sets clearly move around 50% and a decreasing pattern as consideration sets increase in size is not visible.[21] We interpret this as evidence for simultaneous search being the search method

[21] Note that few consumers in the data search 6 or more times. We are not able to calculate std. errors for consideration sets

consumers use.

To provide further evidence of simultaneous search, we adapt a test suggested by De los Santos et al. (2012). In their paper, the authors study data in which not only consideration sets and purchases, but also the sequence of searches is observed. They suggest testing for sequential search using the "price dependece" observation: Under sequential search, if a consumer gets a sufficiently low price draw, he will stop searching. To implement the test, De los Santos et al. (2012) use data on consumers with consideration sets of size one or two and estimate a binary choice model where the dependent variable is the decision to search once or twice and among the regressors is a variable capturing whether the first price was lower or equal to the second. De los Santos et al. (2012) do not find a significant effect of a low first price of consumers' decision to collect a second price quote and view it as evidence for simultaneous search.

We use the same "price dependence" idea to test for sequential search in our data. While we do not observe the sequence of searches, we observe the free first quote consumers got from their previous insurance provider. Under sequential search, consumers who get a below-expectation price quote for that firm should be less likely to actively search other insurance companies. To test this hypothesis, we estimate a binary logit model where the dependent variable captures a consumer's decision to search or not to search beyond the free first quote. Among the regressors is a dummy variable indicating whether the quote provided by the previous insurance provider was below the expected value. Table 13 displays the results. In column A, we control for company-specific fixed effects and in column B, we additionally also control for demographic variables which might influence a consumer's search decision as well. We do not find a significant effect of an above-expectation price on consumer's decision to actively search in either logit regression and interpret it as having found no evidence for sequential search.

7.3 Model Overview

Given the assumption of consumer's knowledge of the price his previous insurer is going to charge him, we need to adapt the estimation of the simultaneous search model compared to the Monte Carlo studies. We refer the reader to Honka (2013) for the details of how we estimate the simultaneous search model with auto insurance data. For the sequential search model, we refer the reader to Appendix D of this paper.

7.4 Results

Column A in Table 14 shows the results under the assumption that all consumers search simultaneously, column B shows the results under the assumption that all consumers search sequentially. Costs per search

of size 9 or 10 since only one consumer makes that many searches in each case.

are \$42.09 under simultaneous and \$.73 under sequential search.[22] The simultaneous search model fits the data better than the sequential search model. Note that the search cost estimate under simultaneous search is similar to the one (\$40.85) found by Honka (2013) using the same data and the same model (Model 1 in her paper). The small difference in search cost estimates can be explained by the different assumptions on the price distributions noted previously. Our results are similar to the findings in the simulation studies (section 6.3) where we found the search cost estimate to be biased downwards when the incorrect type of search is assumed. Given that we found model-free evidence for simultaneous search in the data in subsection 7.2 , the search cost estimate under sequential search is likely to be biased downwards. In contrast to Hong and Shum (2006), we find search costs under sequential search to be smaller than under simultaneous search. The difference in the relation of the search costs under both search methods can be explained by consumers searching for the lowest price in Hong and Shum (2006), while we assume a full utility specification and consumer utility maximization.

As discussed in the Identification subsection on sequential search, the effects of demographic variables that do not vary across companies are not identified in the utility function under sequential search. We therefore estimate a simultaneous and sequential search model where those demographic effects enter through consumers' search costs instead of utility. The results are shown in columns A and B and Table 15. We find that for the simultaneous search model the estimates and the loglikelihoods are very similar to column A in Table 14. For the sequential search model, we find - as expected - the inclusion of the two demographic variables to increase the loglikelihood. Additionally, both AIC and BIC support the inclusion of both variables. The other parameter estimates remain very similar to column B in Table 14.

The sequential search model is also more flexible in that we do not have to assume first-order stochastic dominance among the price distributions in order to be able to estimate it. Thus we estimate it using company-specific price variances (column C in Table 15). We neither find the estimates nor the loglikelihood to change much compared to column B in Table 14. This is likely due to the company-specific price variance being similar. Finally, in column D of Table 15, we estimate a sequential search model with company-specific price variance and consumer-specific demographic variables entering the model through search costs. While we find the loglikelihood to increase, this increase is due to the inclusion of additional demographic variables. Further, we find that the loglikelihood of the most flexible sequential search model (column D) is still much smaller than the one of the less flexible simultaneous search model (column A in Table 14).

[22] We calculate search costs in dollars by dividing the search cost coefficient c by the price coefficient β_1.

7.5 Search Cost Elasticities

We use simulation methods to calculate search cost elasticities. We use the model estimates under both simultaneous and sequential search and predict the percentage change in companies' market shares due to a 10% increase in search costs. Note that in the auto insurance market the search cost elasticity for purchase across all companies (in terms of purchased quantity) is zero because consumers are required to have auto insurance. Thus the total number of purchased auto insurance policies does not vary with search costs. The company-specific search costs elasticities for purchase can be both positive and negative. Two effects determine search cost elasticities: First, some companies benefit from an increase in search costs because a consumer searches fewer companies due to the higher search costs, there is less competition within this consumer's consideration set and the company gets newly chosen by the consumer. Second, some companies are hurt by an increase in search costs as a consumer decides to search fewer companies due to the increase in search costs and the company no longer gets searched and thus purchased. All companies encounter both effects when search costs increase and the net effect determines whether the company-specific search cost elasticity is positive or negative. Our numbers below need to be interpreted in light of this tradeoff for each company.

A 10% (100%) increase in search costs results in a 1.61% (42.27%) decrease in the average number of actively searched companies under simultaneous search, i.e. excluding the free quote from the previous insurance provider. A 10% (100%) increase in search costs results in a 4.02% (28.37%) decrease in the average number of actively searched companies under sequential search.

Table 16 shows percentage changes in consideration and purchase market shares due to a 10% increase in search costs under both types of search. In general, a 10% increase in search costs has a larger effect on market shares under sequential than simultaneous search. There are only a few companies (Erie, Geico, Mercury, Travelers) whose consideration and purchase market shares move in the same direction under both types of search. Given a search method, consideration and purchase market shares do not necessarily move in the same direction (e.g. Metlife, Nationwide and Progressive under simultaneous and Allstate, American Family and Safeco under sequential search). When it comes to purchase, Allstate, American Family, Erie and Mercury lose market shares and Geico, Liberty Mutual, Progressive and Travelers gain market shares under both search methods. When search costs increase, Geico and Progressive are better off when consumers search sequentially where these firms are able to increase their market shares, while Allstate and State Farm are better off when consumers search simultaneously as these firms lose less market share compared to the other search method.

8 Counterfactuals

8.1 How are companies affected by a change in customers' search method?

In this first counterfactual, we explore whether and how insurance companies are affected by a change in consumers' search method. Why would consumers change their search method? The main advantage of the simultaneous search model is also the primary disadvantage of the sequential search model, namely that prices can be gathered quickly. So in a situation where a consumer needs to obtain prices quickly, we expect him to prefer searching simultaneously. Furthermore, Chade and Smith (2006) and Kircher (2009) find that using simultaneous search is more efficient for consumers when the other side of the market might reject the consumer. So we expect a consumer to be more likely to search simultaneously if (a) the amount of time the consumer has to gather the price quotes is limited and (b) if there is a concern that the firm or the seller might reject the customer. Variables that translate into these two factors in the insurance market are potentially the timing of the price search process (close to the policy expiration date or weeks in advance), tickets and accidents in the past and low credit scores. So if a consumer receives a number of tickets in the year prior to renewal, we would expect him to be more likely to engage in simultaneous search. We explore how companies' market shares and the composition of their customer base changes as a result of a change in consumers' search method. SHOULD WE SAY SOMETHING ALONG THE LINES THAT TO THE EXTENT THAT INSURANCE COMPANIES OBSERVE THIS INFORMATION, THEY MIGHT WANT TO PRESENT INFORMATION DIFFERENTLY TO DIFFERENT "TYPES" OF CONSUMERS?

8.1.1 Effects on Market Shares

To study the question how companies' market shares change when consumers change their search method, we predict consumers' consideration sets and purchases using our data on consumers shopping for auto insurance and the parameter estimates from Table 14 where we assumed that all consumers search either simultaneously or sequentially.

Table 17 shows the actual and predicted consideration sets and purchases under the assumption that simultaneous search is the true DGP. Additionally, the columns labeled "Seq. Search" in Table 17 also show the predicted consideration sets and purchases under sequential search keeping all utility and search cost parameter estimates the same as under simultaneous search, i.e. only changing the search method. The average predicted consideration set size under simultaneous and sequential search is 2.99 and 1.74, respectively, compared to 2.96 in the data. The drop in the average consideration set size is due to the significantly larger search cost estimate under simultaneous versus sequential search. Recall that to reconcile the number of brands in the consideration set with the sequential search strategy required a much smaller search cost estimate (.0005 vs. .1885 under simultaneous search).[23] Similar to the results from the Monte Carlo simulation displayed in column (A) in Table 6 where the true DGP consisted of simultaneous search, but we assumed sequential search for the estimation in order to fit the data under sequential search, a much smaller search cost coefficient is estimated. For example in column (A) in Table 6, the true search costs are .3 and the estimated search cost coefficient is .02.[24] A similar picture is seen in column (A) in Table 14: The search cost coefficient under simultaneous search is much larger than the one under sequential search. Therefore, when we use the signficantly larger search cost estimate (and the utility parameter estimates) from the simultaneous search model to make consideration and purchase market share predictions under sequential search, we find consumers mostly not to actively search at all and to only consider their previous insurance provider (as reflected in their consideration set size of 1.74). Since consumers only consider one company (their previous insurer), they also purchase from this company and the consideration set and purchase market shares under sequential search are very similar. We regard this as a peculiarity of the auto insurance industry which is characterized by a high retention rate. The average retention rate we observe in our data is 74% which is not atypical for this industry (see Honka, 2013, and Israel, 2005) and is also reflected by the large inertia coefficient in the estimation results.

Let us assume that simultaneous search is the true underlying search method and correctly reflects the utility parameters and search costs of all consumers in the market. If consumers then decide to change their search method, i.e. to search sequentially, we find three of the four largest insurance companies, namely Geico, Progressive, and State Farm to gain market share (see last column in Table 17).[25] These customers decide to switch from their smaller previous insurers to the larger insurance companies as a result of the different search method.

Similar to Table 17, we show the actual and predicted consideration sets and purchases under the assumption that sequential search is the true data generating process in Table 18. Additionally, the columns labeled "Sim. Search" in Table 18 also show the predicted consideration sets and purchases under simultaneous search keeping all utility and search cost parameter estimates the same as under sequential search, i.e. only changing the search method. The average predicted consideration set size under simultaneous and sequential search is 2.96 and 3.36, respectively, compared to 2.96 in the data.

In contrast to the Monte Carlo simulation displayed in column (B) in Table 6 where the true DGP consisted of sequential search, but we assumed simultaneous search for the estimation in order to fit the data under simultaneous search, a much larger search cost coefficient is estimated. For example in column (B) in

[23]This also holds for search costs in dollars, i.e. search cost coefficient c divided by the price coefficient β_1, which are \$.73 under sequential and \$42.09 under simultaneous search.

[24]This again also holds for search costs in dollars, i.e. search cost coefficient c divided by the price coefficient β_1.

[25]We also find AIG and Mercury to gain market share.

Table 6, the true search costs were .3 and the estimated search cost coefficient was .00, while in the estimation with insurance data we find the search cost coefficient under simultaneous search to be .1885, while it is .0005 under sequential search. There are two possible explanations for this results: The first explanation is that the true DGP for the auto insurance market is simultaneous search and the second explanation is that search cost estimates can be biased up- or downward when the true DGP is sequential search, but simultaneous search is assumed for the estimation depending on the data characteristics and the true utility parameters.

Let us assume that sequential search is the true underlying search method and correctly reflects the utility parameters and search costs of all consumers in the market. If consumers then decide to change their search method, i.e. to search simultaneously, we find a reversal of our previous results: The same three large auto insurance companies, namely Geico, Progressive and State Farm, which gained market share when consumers switched from searching simultaneously to searching sequentially, now lose market share when consumers switch from searching sequentially to searching simultaneously (see last column in Table 18).[26]

To summarize we find that three out of the four largest insurance companies, namely Geico, Progressive and State Farm, are better off, i.e. have a higher market share, when consumers search sequentially, while smaller insurance companies are better off when consumers search simultaneously. This is a similar result to Farag et al. (2004) who found that market followers do not suffer when consumers also search market leaders, but that market leaders suffer when consumers search market followers.

8.1.2 Effects on customer base

To study the effects of a change in consumers' search method on insurance companies' customer base, we explore whether some companies get more or fewer "risky" customers as well as how other customer and policy characteristics change depending on the type of search consumers use. Knowing the characteristics of your customer base is important in any industry to understand who your customers are, what their willingness-to-pay is and how to target them, but it is particularly important in the insurance industry where consumer chatacteristics directly influence an insurance company's revenues and costs through consumer-specific premia and claim likelihood. We therefore consider consumer characteristics that are known to be important cost shifters for insurance companies as well as other consumer characteristics which describe an insurance company's customer base. To evaluate "riskiness" of an insurance company's customer base, we consider the percentage of drivers with accidents and tickets in the past three years and the percentage of policies with a driver under 25 years. To evaluate other customer and policy characteristics, we look at the average number of drivers and vehicles on the policy, the percentage of consumers living in an urban area and the average age of the primary policy holder.

[26] Mercury and Safeco also lose market share when consumers switch from searching simultaneously to searching sequentially.

Table 19 shows the results assuming that the true DGP is simultaneous search and explores how each company's customer bases change when consumers switch to sequential search (keeping all utility and search cost parameters the same as under simultaneous search). Recall from the previous counterfactual that we found the three of the four largest insurance companies (and AIG and Mercury) to gain market share when consumers change their search method. In this counterfactual, we additionally find that the customers these five companies are gaining are mostly high-risk customers (as measured by accidents, tickets, and drivers under 25 years) leaving them with a higher proportion of high-risk customers.[27] Those two results taken together show a mixed picture of a change in search method for these companies: They gain market share, but these new customers are mostly high risk.

The results regarding the other consumer characteristics are mixed: While the percentage of urban drivers decreases for AIG, Mercury and Progressive, it increases for Geico and State Farm. The new customer base at Geico and Progressive is older, while average age decreases for AIG, Mercury and State Farm. The size of insurance policies as measured by the average number of drivers and vehicles on the policy increases for Mercury and State Farm and decreases for AIG and Progressive. The largest differences in the other companies' customer bases can be found for Erie, Metlife and Travelers. For these three companies, their customer base as measured by the proportion of customers with accidents and tickets and drivers under 25 years of age becomes much more risky. While the size of the average insurance policy as measured by the average number of drivers and vehicles on the policy remains relatively constant, Erie and Travelers gain younger, urban customers, while Metlife gains customers living in rural and suburban areas.

Table 20 shows the results assuming that the true DGP is sequential search and explores how each company's customer base changes when consumers switch to simultaneous search (keeping all utility and search cost parameters the same as under sequential search). We find a mixed picture for the customer base of the five companies which lose market share when consumers switch from searching sequentially to searching simultaneously, namely Geico, Progressive, State Farm, Mercury and Safeco: Some of them are left with a smaller, but less risky customer base (e.g. Geico) and some are left with fewer and more risky customers (e.g. Progressive, Mercury).

The results regarding other consumer characteristics are mixed: The average insurance policy size remains relatively constant for all five companies that lose market share when consumers switch from searching sequentially to searching simultaneously. For both Mercury and Safeco, their customer base becomes younger and more urban as a result of the change in search method. Among the companies that gain market share, the biggest changes are seen for 21st Century, GMAC and Travelers. 21st Century's customers become younger and more urban buying smaller insurance policies. GMAC's customers become older and more

[27] Exceptions are Progressive and to some extent State Farm.

urban having fewer drivers, but more cars on their insurance policies. Traveler's customers become older and less urban buying smaller insurance policies.

An obvious question would be how a firm can potentially influence the search strategy used by consumers. Insurance companies typically send renewal notices to their current customers about one month before their customers' insurance policy is about to expire. Further, a few insurance companies such as Progressive or Esurance, let customers get approximate insurance quotes from competitors through their websites. Following these strategies, they can potentially influence the search strategies being used by customers.

9 Limitations & Future Research

There are several limitations to our research. While our data allow us to say something about the type of search consumers engage in, we do not observe the actual search sequence. Unlike in online environments (e.g., De los Santos et al. 2012) where one might observe the search process, such information is usually not available in most product categories. Consequently, our assessment of the search method consumers engage in is limited by the data available.

We assume that consumers have rational expectations about prices. A model that has information on consumer price expectations or is able to recover them would enable researchers to test the hypothesis of rational price expectations and compare it with other price expectation formation theories. Our model implicitly assumes that consumers make one and only one decision about the search method they want to use (and the number of quotes they are going to collect under simultaneous search) before starting any search activity. In reality, consumers might go through multiple search stages. For example, a consumer might initially decide to collect two price quotes searching simultaneously and, after learning about the two prices, decide to search sequentially, stop after three price quotes and make a purchase. Developing such a multi-stage search model is left for future research. To carry out such analyses however, researchers need to be equipped with more detailed data than those used in this paper. At the same time, the data we use are increasingly becoming available; the approaches proposed in this paper therefore, allow us to make some progress on answering imporatant questions regarding the magnitudes of search costs as well as consequences of assumptions made in estimating models of search.

Following the standard search literature our model assumes that consumers search to resolve uncertainty about a single product characteristic, e.g. price. But in many contexts, consumers might search to learn about two or more product characteristics. For example, consumers might search to learn about coverage options and prices in the auto insurance industry. We leave it for future research to develop a model which allows consumers to search for two or more product characteristics. While our empirical model incorporates rich details on observed heterogeneity, we cannot accommodate unobserved heterogeneity across consumers with our data. Honka (2013) fits a full random coefficients model to the auto insurance data and finds that this does not change the conclusions of her simultaneous search model.

10 Conclusion

In this paper, we explore whether the type of search consumers use can be deduced from data sets where consumer purchases and consideration sets, but not the sequence of searches, are observed. We show analytically that the search method is identified in those kind of data. Under simultaneous search, the average proportion of below-expectation price draws is constant across all consideration set sizes, while under sequential search, the average proportion of below-expectation price draws decreases as consideration sets increase in size. Using an extensive set of simulation studies, we also find that the model fit points us to the true type of search. Additionally, we extend our simulations to assess the consequences of various assumptions made by researchers when formulating and estimating search models.

We suggest a new estimation approach for the sequential search model where the researcher has access to individual-level data on consideration sets, purchases, and other characteristics, but not the sequence of searches. Our simulated maximum likelihood estimation approach is able to overcome the challenge of the researcher not knowing the sequence of searches.

We apply our model and estimation approach to data from the U.S. auto insurance industry and find consumers to search simultaneously with search costs of about \$42. Using our estimates we study how insurance companies are affected when consumers change their search methods. We find that the largest insurance companies are better off when consumers search sequentially, while smaller companies profit from consumers searching simultaneously.

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Figures

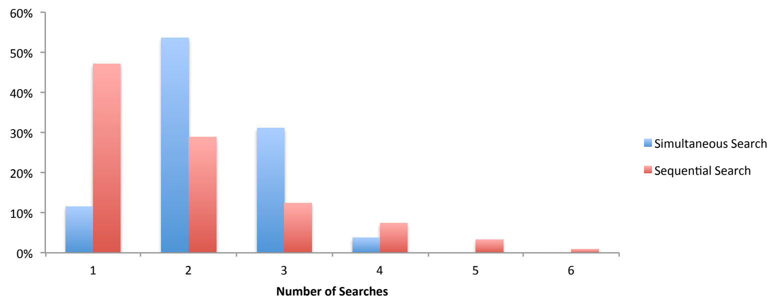

Figure 1: Number of Searches Histograms

Tables

Consideration Set Size	1	2	3	4	5	6
Pure Price Search						
% Below-Average Actual Prices Under						
Sim. Search		50.13	47.47			
Seq. Search	100.00	57.76	38.86	21.72	12.73	5.93
100% (1/Consideration Set Size)	100.00	50.00	33.33	25.00	20.00	16.67
Differentiated Goods						
% Below-Average Actual Prices Under						
Sim. Search	50.40	50.90	49.80	51.30		
Seq. Search	86.60	49.90	39.80	30.40	27.90	25.90
100% (1/Consideration Set Size)	100.00	50.00	33.33	25.00	20.00	16.67

Table 1: Intuition for Search Method Identification

	(A) Simultaneous Search	**(B)** Searches Search	**(C)** Change in Consideration Percentages
Brand 1	35.1	29.6	-15.7
Brand 2	73.9	63.5	-14.1
Brand 3	45.6	38.3	-16.0
Brand 4	24.0	20.3	-15.4
Brand 5	31.8	28.3	-11.0
Brand 6	16.8	13.6	-19.0

Table 2: Consideration Percentages in %

	(A)	(B)	(C)	(D)	(E)
	Purchase Market Shares		**Conversation Rates**		Change in
	Sim. Search	Seq. Search	Sim. Search	Seq. Search	Conversation Rates
Brand 1	14.0	13.8	39.9	46.6	16.9
Brand 2	39.1	36.6	52.9	57.6	8.9
Brand 3	17.6	19.3	38.6	50.4	30.6
Brand 4	10.0	10.2	41.7	50.2	20.6
Brand 5	13.7	13.8	43.1	48.8	13.1
Brand 6	5.6	6.3	33.3	46.3	39.0

Table 3: Purchase Market Shares and Conversation Rates and Their Change in %

	% Customer Base that Changes		
Brand 1	50.4		
Brand 2	25.3		
Brand 3	42.7		
Brand 4	46.3		
Brand 5	37.1		
Brand 6	58.7		
	Av. Number of Searches Among Customers		
	Simultaneous Search	Sequential Search	Change in %
Brand 1	2.4	2.1	-14.9%
Brand 2	2.2	1.6	-25.1%
Brand 3	2.2	2.1	-7.2%
Brand 4	2.4	2.2	-10.8%
Brand 5	2.3	2.2	-7.3%
Brand 6	2.5	2.3	-6.1%

Table 4: Changes in Customer Base

		(A)		(B)	
DATA GENERATION		Simultaneous Search		Sequential Search	
ESTIMATION		Simultaneous Search		Sequential Search	
POPULATION 1	True Values	Means	S.E.	Means	S.E.
Brand Intercept 1	-2.0	-1.99	0.14	-1.96	0.14
Brand Intercept 2	-1.6	-1.72	0.14	-1.61	0.14
Brand Intercept 3	-2.1	-2.07	0.13	-2.05	0.13
Brand Intercept 4	-2.4	-2.27	0.13	-2.31	0.17
Brand Intercept 5	-1.4	-1.59	0.15	-1.44	0.18
Brand Intercept 6	-1.8	-1.77	0.15	-1.75	0.15
Advertising	0.5	0.47	0.03	0.45	0.06
Price	-1.0	-0.96	0.04	-0.94	0.08
Search Cost	0.3	0.28	0.03	0.28	0.05
Loglikelihood		-3,545.06		-3,213.38	

Table 5: Monte Carlo Studies Results with Known Type of Search

DATA GENERATION ESTIMATION		(A) Simultaneous Search Sequential Search		(B) Sequential Search Simultaneous Search	
	True Values	Means	S.E.	Means	S.E.
Brand Intercept 1	-2.0	-2.34	1.58	-2.05	0.04
Brand Intercept 2	-1.6	-2.19	1.58	-1.85	0.07
Brand Intercept 3	-2.1	-2.33	1.58	-1.84	0.04
Brand Intercept 4	-2.4	-2.49	1.60	-2.18	0.04
Brand Intercept 5	-1.4	-1.73	1.59	-1.32	0.07
Brand Intercept 6	-1.8	-2.15	1.60	-2.04	0.07
Advertising	0.5	0.38	0.08	0.35	0.03
Price	-1.0	-0.35	0.03	-0.10	0.00
Search Cost	0.3	0.02	0.01	0.00	0.00
Loglikelihood		-4,452.56		-3,555.97	

Table 6: When the Wrong Type of Search is Assumed

DATA GENERATION ESTIMATION		(A) Simultaneous Search Sequential Search		(B) Sequential Search Simultaneous Search	
	True Values	Means	S.E.	Means	S.E.
Brand Intercept 1	-2.0				
Brand Intercept 2	-1.6				
Brand Intercept 3	-2.1				
Brand Intercept 4	-2.4				
Brand Intercept 5	-1.4				
Brand Intercept 6	-1.8				
Advertising	0.5				
Price	-1.0				
Search Cost	0.3	0.24	0.01	0.37	0.00
Loglikelihood		-5,353.44		-3,752.97	

Table 7: All Parameters, but Search Costs Fixed

		(A)		(B)		(C)	
DATA GENERATION		Unequal Variances Sequential Search		Unequal Variances Simultaneous Search		Unequal Variances Sequential Search	
ESTIMATION		Unequal Variances Sequential Search		Equal Variance Simultaneous Search		Equal Variance Sequential Search	
	True Values	Means	S.E.	Means	S.E.	Means	S.E.
Brand Intercept 1	-2.0	-1.88	.17	-2.69	.11	-2.66	.29
Brand Intercept 2	-1.6	-1.62	.13	-2.09	.11	-1.79	.29
Brand Intercept 3	-2.1	-2.05	.14	-2.03	.09	-1.98	.27
Brand Intercept 4	-2.4	-2.27	.15	-2.08	.09	-2.36	.25
Brand Intercept 5	-1.4	-1.53	.14	-1.13	.11	-1.43	.26
Brand Intercept 6	-1.8	-1.83	.13	-1.19	.11	-1.40	.25
Advertising	0.5	.47	.05	.35	.03	.20	.08
Price	-1.0	-.91	.07	-.25	.01	-.62	.07
Search Cost	0.3	.23	.04	.01	.00	.13	.04
Loglikelihood		-3,338.65		-3,792.12		-3,570.45	

Table 8: Equal Variance Assumption

		(A)		(B)		(C)	
DATA GENERATION		Company-Specific Search Costs Sequential Search		Company-Specific Search Costs Simultaneous Search		Company-Specific Search Costs Sequential Search	
ESTIMATION		Company-Specific Search Costs Sequential Search		Identical Search Costs Simultaneous Search		Identical Search Costs Sequential Search	
	True Values	Means	S.E.	Means	S.E.	Means	S.E.
Brand Intercept 1	-2.0	-2.01	.07	-2.03	.05	-2.04	.17
Brand Intercept 2	-1.6	-1.65	.10	-1.51	.07	-1.68	.24
Brand Intercept 3	-2.1	-2.11	.07	-1.34	.04	-1.54	.19
Brand Intercept 4	-2.4	-2.39	.07	-2.51	.05	-2.47	.19
Brand Intercept 5	-1.4	-1.40	.05	-2.08	.08	-1.70	.26
Brand Intercept 6	-1.8	-1.81	.05	-1.88	.08	-1.75	.19
Advertising	0.5	.38	.05	.35	.03	.47	.07
Price	-1.0	-.90	.05	-.41	.02	-.73	.08
Search Cost 1	0.3	.28	.03	.03	.00	.15	.04
Search Cost 2	0.2	.21	.04				
Search Cost 3	0.1	.11	.02				
Search Cost 4	0.4	.38	.04				
Search Cost 5	0.5	.53	.05				
Search Cost 6	0.3	.30	.03				
Loglikelihood		-3,015.95		-3,345.06		-3,165.00	

Table 9: Identical Search Cost Assumption

Variable	**N**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Number of Quotes	945	2.96	1.38	1	10
Premium for 6-months Policy with PI	270	756.41	365.10	105.00	2,700.00
Premium for 6-months Policy with CI (same sample as PI)	270	554.49	265.90	89.00	2,750.00
Premium for 6-months Policy with CI	945	592.97	288.28	74.00	2,750.00
Number of Vehicles with CI	945	1.58	0.64	1	3
Number of Drivers with CI	945	1.64	0.59	1	4
Number of Years with CI	945	7.07	9.04	0	50
Vehicle Year	945	2001.98	4.19	1960	2007
Respondent Age	945	45.23	12.94	20	84

Table 10: Descriptive Statistics
PI: Previous Insurer; CI: Current Insurer

Variable	Coefficient	Std. Error	**Variable**	Coefficient	Std. Error
Constant	2.2886b	(.7624)	21st Century	.2374	(.5118)
Male	-.2063	(.1574)	AIG	.4593	(.4107)
Marital Status: Married	-.8474b	(.2718)	Allstate	-.1791	(.3049)
Marital Status: Divorced/ Separated	-.1308	(.2635)	American Family	-.6157	(.5088)
Marital Status: Widowed	.3808	(.7642)	Erie	-1.3207a	(.5062)
Marital Status: Domestic Partnership	-.1202	(.3344)	Farmers	-.3980	(.3936)
Age	-.0224a	(.0065)	Geico	-1.0452a	(.2972)
Driver under 25	1.0810b	(.3316)	GMAC	.6378	(.6153)
Two Vehicles	2.0683a	(.1986)	The Hartford	-.7291	(.4461)
Three Vehicles	4.1097a	(.3031)	Liberty Mutual	.3033	(.3907)
Two Drivers	.3489	(.2683)	Mercury	.2958	(.5137)
Three Drivers	2.0738a	(.4954)	MetLife	.9811d	(.5057)
Four Drivers	1.3158	(.9044)	Nationwide	-.4867	(.3926)
Location: Suburb of a Medium City	.0366	(.2498)	Progressive	-.1205	(.3162)
Location: Suburb of a Large City	.6730b	(.2491)	Safeco	.2390	(.5773)
Location: Urban Area	1.0057a	(.2776)			
Home Owner Insurance with CI	-.1854	(.1720)	Travelers	.7033	(.4416)
Other Insurance with CI	-.2136	(.1746)	Chosen Coverage Dummies	yes	
Two or More Accidents	2.7329a	(.4659)	State	yes	
Two or More Tickets	1.2601a	(.3656)	Make*Class	yes	
Model Age	-.0566b	(.0182)			
R2	.72				

Table 11: Price Distribution
Prices are measured in $100.

Consideration Set Size	1	2	3	4	5	6	7	8	9	10
% Below-Expectation Prices	47.62	48.95	44.17	50.42	50.14	56.94	32.65	56.25	44.44	50.00
Std. Errors	(5.51)	(2.19)	(2.41)	(3.25)	(4.11)	(7.24)	(12.47)	(12.62)	NA	NA

Table 12: Average Proportion of Below-Expectation Prices in Insurance Data

	(A)		(B)	
	Estimate	Std. Error	Estimate	Std. Error
Intercept	2.3354a	(.4395)	1.5623c	(.7070)
Below-Expectation PI Price (0/1)	.1924	(.2351)	.2525	(.2487)
	Company Fixed Effects		Company Fixed Effects	
21st Century	-.8881	(.6198)	-.8629	(.6616)
AIG	.8682	(.8369)	.5395	(.8635)
Allstate	1.3735d	(.8324)	1.3759	(.8513)
American Family	1.0059	(1.1021)	1.3617	(1.1298)
Erie	.2114	(.8471)	.3617	(.8759)
Farmers	-.7002	(.5590)	-.6648	(.5858)
Geico	-.4432	(.5127)	-.4551	(.5390)
GMAC	.0184	(.8517)	-.1816	(.8910)
Hartford	-.5311	(.6110)	-.9393	(.6622)
Liberty Mutual	-.6473	(.5581)	-.7128	(.5952)
Mercury	-1.3307c	(.6357)	-1.6634b	(.6882)
MetLife	-.0993	(.8561)	-.3402	(.9036)
Nationwide	-.1020	(.6335)	-.1730	(.6717)
Progressive	.5246	(.6263)	.4446	(.6578)
Safeco	14.1626	(550.1139)	15.4700	(837.3478)
Travelers	-1.0846d	(.6015)	-1.0059	(.6421)
	Demographics		Demographics	
Age			.0146	(.0106)
Male			-.1124	(.2857)
Income \$25,000 - \$49,999			.2263	(.3530)
Income \$50,000 - \$74,999			-.3383	(.3284)
Income \$75,000 - \$99,999			.8335d	(.4456)
Income \$100,000 - \$149,000			.4597	(.6638)
Income \$150,000 or more			-.7779	(.5373)
Education: High School Graduate			.4997	(.5221)
Education: College Graduate			.6355d	(.3472)
Education: Some Graduate Courses			.1927	(.3133)
Education: Advanced Degree			.5041	(.5001)
Attitude Towards Auto Insurance Shopping & Switching			-.5933a	(.1427)
New Technology Adoption			-.0786	(.1378)
Technology Usage			-.0819	(.1482)
Loyalty			-.0643	(.1482)
Interest in Finance			.2180	(.1652)
Loglikelihood	-259.45		-240.05	

Table 13: Testing for Evidence of Sequential Search
a: <.001, b: <.01, c < .05, d: <.10

	(A) Simultaneous Search		(B) Sequential Search	
	Estimate	Std. Error	Estimate	Std. Error
	Brand Preferences		Brand Preferences	
21st Century	-1.7019a	(.2047)	.3814b	(.1449)
AIG	-1.1634a	(.2005)	.8831a	(.1223)
Allstate	-1.5772a	(.2241)	.8214a	(.1612)
American Family	-1.5522a	(.2204)	.9392a	(.1631)
Erie	-1.8607a	(.2164)	.7687a	(.1584)
Farmers	-1.8135a	(.2064)	.6096a	(.1384)
Geico	-2.1390a	(.2762)	.0801	(.1649)
GMAC	-1.7801a	(.3297)	.7602a	(.1455)
Hartford	-1.6454a	(.1879)	.5208a	(.1238)
Liberty Mutual	-1.5790a	(.2023)	.1565	(.1541)
Mercury	-1.8209a	(.2427)	.3002	(.2401)
MetLife	-1.5956a	(.2369)	.4384b	(.1467)
Nationwide	-1.9770a	(.1951)	1.0862a	(.1318)
Progressive	-1.4661a	(.2173)	-.0955d	(.0500)
Safeco	-2.1445a	(.2422)	.3894b	(.1242)
State Farm	-1.5930a	(.2172)	.9673a	(.1455)
Travelers	-1.5936a	(.1952)	.8484a	(.1340)
	Other Parameters		Other Parameters	
Price in $100	-.4479a	(.0446)	-.0683a	(.0029)
Recall*Advertising in $10,000,000	.1279b	(.0491)	.1303a	(.0119)
Inertia	.7172a	(.0745)	.6274a	(.0361)
Search Cost	.1885a	(.0445)	.0005a	(.0001)
	Demographics		Demographics	
Attitude Towards Auto				
Insurance Shopping & Switching	-.4075b	(.1419)		
New Technology Adoption	-.1604	(.1413)		
Proven Reliability	.3431a	(.0556)	.0100	(.0226)
Out-of-Box Character	.1436b	(.0527)	.0723b	(.0263)
Loglikelihood	-3,079.12		-4,571.58	
AIC	6,208.24		9,193.16	
BIC	6,346.85		9,331.77	

Table 14: Auto Insurance Data Results I with Demographics
a: $<.001$, b: $<.01$, c $< .05$, d: $<.10$

	(A) **Simultaneous Search Demographics in Search Costs**		(B) **Sequential Search Demographics in Search Costs**		(C) **Sequential Search Unequal Price Variances**		(D) **Sequential Search Demo. in SC Unequ. Price Var.**	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
	Brand Preferences		Brand Preferences		Brand Preferences		Brand Preferences	
21st Century	-1.7600a	(.1887)	.2929c	(.1328)	.2496d	(.1413)	.2012	(.1355)
AIG	-1.2198a	(.1876)	.8188a	(.1221)	.8036a	(.1397)	.8200 a	(.1308)
Allstate	-1.6359a	(.2087)	.7493a	(.1544)	.7350a	(.1627)	.7694a	(.1673)
American Family	-1.6130a	(.2388)	.8517a	(.1599)	.8461a	(.1491)	.7023a	(.1599)
Erie	-1.9251a	(.2173)	.6778a	(.1412)	.6510a	(.1499)	.7859a	(.1505)
Farmers	-1.8727a	(.2082)	.5166a	(.1284)	.4932a	(.1384)	.5987a	(.1486)
Geico	-2.2048a	(.2585)	.7799a	(.1593)	.7724a	(.1485)	.4424a	(.1531)
GMAC	-1.8382a	(.2938)	-.0035	(.1774)	-.0042	(.1663)	-.0505	(.1675)
Hartford	-1.7058a	(.1766)	.6840a	(.1531)	.6948a	(.1702)	.6484a	(.1699)
Liberty Mutual	-1.6335a	(.2169)	.4433b	(.1349)	.4244b	(.1475)	.3805c	(.1538)
Mercury	-1.8802a	(.2377)	.1985	(.1542)	.1746	(.1608)	.1470	(.1551)
MetLife	-1.6467a	(.2163)	.2304	(.2004)	.2100	(.2072)	.1644	(.2118)
Nationwide	-2.0378a	(.1845)	.3615c	(.1573)	.3399c	(.1616)	.2977	(.1859)
Progressive	-1.5266a	(.2132)	1.0271a	(.1357)	1.0060a	(.1268)	.9862a	(.1402)
Safeco	-2.1995a	(.2317)	-.1493c	(.0702)	-.0912	(.0617)	-.1547c	(.0719)
State Farm	-1.6474a	(.2059)	.8901a	(.1549)	.8713a	(.1438)	.3142c	(.1527)
Travelers	-1.6503a	(.1867)	.3266c	(.1631)	.3694c	(.1559)	.7492a	(.1494)
	Other Parameters		Other Parameters		Other Parameters		Other Parameters	
Price in $100	-.4518a	(.0445)	-0.0682a	(.0038)	-.0698a	(.0057)	-.0698a	(.0042)
Recall*Advertising								
in $10,000,000	.1288b	(.0480)	.1281a	(.0182)	.1318a	(.0164)	.1244a	(.0162)
Inertia	.7194a	(.0783)	.6008a	(.0290)	.6001a	(.0244)	.5729a	(.0303)
Proven Reliability	.3430a	(.0541)	.0060	(.0229)	.0076	(.0199)	.0102	(.0254)
Out-of-Box Character	.1424b	(.0528)	.0759b	(.0240)	.0802c	(.0353)	.0762b	(.0279)
	Search Costs		Search Costs		Search Costs		Search Costs	
Search Cost Constant	-1.6728a	(.2451)	-6.5425a	(.2811)	-6.2178a	(.3286)	-5.200a	(.3179)
Attitude Towards Auto								
Insurance Shopping & Switching	.3018d	(.1655)	.4272a	(.1379)			.5359a	(.1402)
New Technology Adoption	.0240	(.1535)	-.4830	(.4078)			-.4625	(.3861)
Loglikelihood	-3,082.43		-4,376.46		-4,579.15		-4,237.36	
AIC	6,214.86		8,802.92		9,208.30		8,524.72	
BIC	6,353.47		8,941.53		9,346.91		8,663.33	

Table 15: Auto Insurance Data Results I with Demographics (continued)
a: <.001, b: <.01, c < .05, d: <.10

Company	Simultaneous Search Consideration	Simultaneous Search Purchase	Sequential Search Consideration	Sequential Search Purchase
21st Century	-3.75	-2.00	.28	1.11
AIG	.17	.13	-4.93	-4.77
Allstate	-.22	-.48	.67	-.52
American Family	-.69	-.03	.26	-.90
Erie	-.20	-.07	-1.37	-1.49
Farmers	1.07	.00	-2.54	-1.46
Geico	.16	.45	2.74	1.92
GMAC	1.06	.00	.63	-2.32
The Hartford	.30	.11	-3.27	-2.69
Liberty Mutual	1.07	.24	-1.87	.29
Mercury	-2.00	-4.47	-1.55	-1.27
MetLife	-2.00	1.65	-5.55	-1.88
Nationwide	-.30	.92	.84	-.79
Progressive	-.06	.01	1.40	.63
Safeco	1.06	.00	-1.37	.63
State Farm	.31	.00	-4.07	-.26
Travelers	1.07	.81	.95	.95

Table 16: Search Cost Elasticities in % due to a 10% Increase in Search Costs

	Consideration Set Composition			Purchase Market Shares			
		Predictions			Predictions		
Company	**Data**	**Sim. Search**	**Seq. Search**	**Data**	**Sim. Search**	**Seq. Search**	**Change in %**
21st Century	2.73	1.53	2.06	2.81	2.61	2.28	-12.64
AIG	7.17	8.18	7.48	3.96	5.65	6.83	+20.89
Allstate	12.61	14.24	12.03	14.16	11.96	10.52	-12.04
American Family	2.28	4.18	3.61	2.53	4.24	3.80	-10.38
Erie	1.72	2.91	3.49	2.83	2.93	2.71	-7.51
Farmers	4.09	3.16	3.61	4.92	5.65	3.80	-32.74
Geico	18.58	20.35	21.87	18.41	18.59	23.75	+27.76
GMAC	1.95	.69	.31	1.60	.87	.33	-62.07
The Hartford	4.82	4.80	3.86	4.24	5.33	3.36	-36.96
Liberty Mutual	3.58	2.36	2.80	4.73	5.43	3.15	-41.99
Mercury	1.80	1.20	1.62	2.22	1.74	1.84	+5.75
MetLife	2.20	1.20	1.00	2.29	1.96	1.30	-33.67
Nationwide	4.11	2.69	3.05	3.35	4.89	3.47	-29.04
Progressive	16.19	16.32	18.19	12.42	15.00	18.76	+25.07
Safeco	1.66	.36	.62	1.68	.65	.65	0.00
State Farm	11.81	14.57	13.08	13.18	10.33	11.82	+14.42
Travelers	2.71	1.27	1.31	4.51	2.17	1.63	-24.88

Table 17: Assumption of Simultaneous Search as the True Data Generating Process. Predictions under Sim. and Seq. Search

	Consideration Set Composition			Purchase Market Shares			
		Prediction			Prediction		
Company	**Data**	**Sim. Search**	**Seq. Search**	**Data**	**Sim. Search**	**Seq. Search**	Change in %
21st Century	2.73	.95	1.26	2.81	1.52	.98	+55.10
AIG	7.17	5.21	8.45	3.96	5.75	5.21	+10.36
Allstate	12.61	12.61	11.81	14.16	11.29	10.52	+7.32
American Family	2.28	3.45	3.74	2.53	3.91	3.07	+27.36
Erie	1.72	1.87	3.10	2.83	2.93	1.52	+92.76
Farmers	4.09	2.64	3.65	4.92	5.32	2.71	+96.31
Geico	18.58	24.78	18.52	18.41	23.56	26.36	-10.62
GMAC	1.95	.95	1.45	1.60	1.52	.76	+100.00
The Hartford	4.82	2.24	4.29	4.24	3.80	1.95	+94.87
Liberty Mutual	3.58	2.13	2.77	4.73	3.04	2.39	+27.20
Mercury	1.80	.92	1.48	2.22	.98	1.41	-30.50
MetLife	2.20	1.47	2.74	2.29	1.74	1.63	+6.75
Nationwide	4.11	2.53	3.19	3.35	4.13	2.71	+52.40
Progressive	16.19	22.07	17.42	12.42	18.57	24.51	-24.24
Safeco	1.66	.40	.77	1.68	.22	.76	-71.05
State Farm	11.81	14.52	13.45	13.18	10.21	12.04	-15.20
Travelers	2.71	1.28	1.90	4.51	1.52	1.52	0.00

Table 18: Assumption of Sequential Search as the True Data Generating Process. Predictions under Sim. and Seq. Search

Company	Search Method	% Drivers with Accidents	% Drivers with Tickets	% Driver Under 25 Years	Av. Number of Drivers	Av. Number of Vehicles	% Drivers in Urban Area	Av. Age
21st Century	Sim.	0.00	8.33	8.33	1.71	1.63	45.83	43.58
21st Century	Seq.	1.59	4.76	9.52	1.62	1.57	38.10	46.05
AIG	Sim.	0.00	5.77	3.85	1.81	1.73	21.15	50.42
AIG	Seq.	3.09	7.94	6.35	1.67	1.71	20.63	48.37
Allstate	Sim.	3.64	5.46	10.00	1.67	1.61	22.73	46.32
Allstate	Seq.	5.71	5.16	10.31	1.68	1.68	20.62	45.78
American Family	Sim.	7.69	5.13	15.38	1.59	1.46	25.64	41.85
American Family	Seq.	8.00	5.71	14.29	1.69	1.60	20.00	41.94
Erie	Sim.	0.00	0.00	18.52	1.85	1.89	14.81	45.22
Erie	Seq.	2.86	4.00	20.00	1.88	1.76	20.00	43.88
Farmers	Sim.	0.00	3.85	3.85	1.67	1.48	23.08	46.33
Farmers	Seq.	1.37	5.71	2.86	1.63	1.46	34.29	45.86
Geico	Sim.	2.34	2.92	5.26	1.58	1.60	21.64	44.11
Geico	Seq.	0.00	3.65	8.22	1.68	1.59	23.74	46.68
GMAC	Sim.	0.00	0.00	0.00	1.88	1.88	12.50	54.25
GMAC	Seq.	0.00	0.00	33.33	2.33	2.00	0.00	43.00
The Hartford	Sim.	0.00	0.00	8.16	1.90	1.92	24.49	60.04
The Hartford	Seq.	3.35	0.00	16.13	1.94	1.87	16.13	60.68
Liberty Mutual	Sim.	4.00	6.00	12.00	1.72	1.74	8.00	48.00
Liberty Mutual	Seq.	0.00	0.00	17.24	1.73	1.76	0.00	45.97
Mercury	Sim.	0.00	0.00	6.25	1.69	1.69	18.75	51.38
Mercury	Seq.	0.00	0.00	11.76	1.88	1.77	11.76	51.18
MetLife	Sim.	0.00	5.56	11.11	1.72	1.78	16.67	49.61
MetLife	Seq.	3.13	8.33	16.67	1.67	1.83	8.33	50.25
Nationwide	Sim.	0.00	4.44	8.89	1.91	1.78	22.22	42.78
Nationwide	Seq.	3.47	6.25	3.13	1.75	1.81	21.88	47.84
Progressive	Sim.	5.80	5.07	13.04	1.72	1.62	17.39	41.46
Progressive	Seq.	4.24	2.89	6.36	1.68	1.58	17.34	42.87
Safeco	Sim.	0.00	0.00	0.00	1.83	1.67	0.00	49.17
Safeco	Seq.	0.00	0.00	0.00	1.67	1.50	33.33	35.83
State Farm	Sim.	1.05	6.32	5.26	1.51	1.35	21.05	46.09
State Farm	Seq.	1.84	5.51	4.59	1.57	1.49	21.10	45.98
Travelers	Sim.	0.00	0.00	5.00	1.70	1.65	10.00	49.35
Travelers	Seq.	0.00	6.67	6.67	1.67	1.53	13.33	40.50

Table 19: Consumer Characteristics under the Assumption of Simultaneous Search as the True Data Generating Process

Company	Search Method	% Drivers with Accidents	% Drivers with Tickets	% Driver Under 25 Years	Av. Number of Drivers	Av. Number of Vehicles	% Drivers in Urban Area	Av. Age
21st Century	Sim.	0.00	7.14	7.14	1.50	1.43	64.29	39.93
21st Century	Seq.	0.00	11.11	11.11	1.67	1.78	11.11	46.11
AIG	Sim.	0.00	3.78	3.77	1.72	1.70	16.98	50.62
AIG	Seq.	2.08	12.50	6.25	1.63	1.69	18.75	48.52
Allstate	Sim.	1.89	4.81	12.50	1.65	1.64	23.08	46.12
Allstate	Seq.	2.06	2.06	8.25	1.70	1.68	22.68	46.42
American Family	Sim.	3.85	2.78	16.67	1.64	1.44	27.78	42.39
American Family	Seq.	3.57	7.14	17.86	1.71	1.61	21.43	41.89
Erie	Sim.	5.56	0.00	18.52	1.85	1.89	14.81	46.85
Erie	Seq.	0.00	0.00	14.29	2.14	1.79	14.29	46.64
Farmers	Sim.	0.00	2.04	2.04	1.78	1.57	22.45	44.73
Farmers	Seq.	4.00	4.00	4.00	1.68	1.52	32.00	45.36
Geico	Sim.	0.00	5.99	6.91	1.66	1.63	23.96	45.26
Geico	Seq.	2.06	3.70	7.00	1.67	1.61	22.63	47.13
GMAC	Sim.	2.30	0.00	7.14	2.07	1.86	7.14	51.71
GMAC	Seq.	0.00	0.00	14.29	2.29	1.71	0.00	45.00
The Hartford	Sim.	0.00	0.00	14.29	2.00	1.94	17.14	61.00
The Hartford	Seq.	0.00	0.00	22.22	2.00	1.83	11.11	60.11
Liberty Mutual	Sim.	0.00	3.57	3.57	1.61	1.61	7.14	49.96
Liberty Mutual	Seq.	4.55	0.00	22.73	1.73	1.68	4.55	48.82
Mercury	Sim.	3.57	0.00	11.11	1.78	1.78	11.11	56.89
Mercury	Seq.	0.00	0.00	7.69	1.85	1.69	15.38	51.08
MetLife	Sim.	0.00	6.25	6.25	1.56	1.75	6.25	48.81
MetLife	Seq.	0.00	6.67	13.33	1.60	1.80	20.00	45.60
Nationwide	Sim.	2.63	2.63	5.26	1.79	1.74	18.42	43.32
Nationwide	Seq.	4.00	8.00	4.00	1.72	1.88	16.00	49.68
Progressive	Sim.	3.51	4.68	10.53	1.67	1.61	20.47	42.92
Progressive	Seq.	2.66	3.54	9.29	1.69	1.59	21.68	43.59
Safeco	Sim.	0.00	0.00	0.00	2.00	2.00	0.00	41.50
Safeco	Seq.	0.00	0.00	0.00	1.57	1.43	28.57	34.71
State Farm	Sim.	2.13	5.32	4.26	1.52	1.36	17.02	45.55
State Farm	Seq.	2.70	5.41	4.51	1.60	1.53	18.92	45.70
Travelers	Sim.	0.00	0.00	14.29	1.86	1.64	7.14	47.29
Travelers	Seq.	7.14	7.14	7.14	1.57	1.43	14.29	39.93

Table 20: Consumer Characteristics under the Assumption of Sequential Search as the True Data Generating Process

Appendix A: Sequential Search Model Estimation

We use simulated maximum likelihood (SMLE) to estimate our model. The probability of observing a consumer search a set of companies Υ and purchase from company j under sequential search is

$$\Pr\left(S_i = \Upsilon \cap y_i = j \,|\, adv_{ij}, \mu_{ij}^p, \sigma_p, p_{ij}, S_i; \theta\right)$$

$$= \Pr\Big(\min_{j \in S_i} u_{ij}^* \geq \max_{j' \notin S_i} u_{ij'}^* \quad \cap \quad \max_{j \in S_i} u_{ij} \geq u_{ij''}, \max_{j' \notin S_i} u_{ij'}^* \quad \cap$$

$$\bigcap_{l=2}^{k} \max_{t<l} \hat{u}_{it} < \hat{u}_{it=l}^* \quad \forall j'' \in S_i \setminus \{j\}, t = 2, \ldots, k \quad \Big)$$

with $\theta = \{\alpha_{ij}, \beta_1, \beta_2, c\}$. The probability does not have a closed-form solution and is non-smooth. Since common optimization routines require smoothness, the non-smooth probabilities would either require using non-gradient based optimization methods or taking a very large number of draws (simple frequency simulator, McFadden, 1989). Instead, we chose to smooth the probabilities using a scaled multivariate logistic CDF (Gumbel, 1961)

$$F(w_1, \ldots, w_M; s_1, \ldots, s_M) = \frac{1}{1 + \sum_{m=1}^{M} \exp(-s_m w_m)} \qquad \forall\, m = 1, \ldots, M$$

where $s_1, \ldots, s_M$ are tuning parameters. McFadden (1989) suggests this kernel-smoothed frequency simulator which satisfies the summing-up condition, i.e. probabilities sum up to 1, and is asymptotically unbiased.

We now describe the step-by-step implementation of the kernel-smoothed frequency simulator.

1. Take $q = 1, \ldots, Q$ draws from ϵ_{ij} (for each consumer/ company combination)

2. For each ϵ_{ij} draw, calculate ω_{qm}

   (a) $\omega_{q1} = \min_{j \in S_i} u_{ij}^* - \max_{j' \notin S_i} u_{ij'}^*$

   (b) $\omega_{q2} = \max_{j \in S_i} u_{ij} - u_{ij''}, \max_{j' \notin S_i} u_{ij'}^*$

   (c) $\omega_{q3 \ldots M} = \bigcap_{l=2}^{T} \max_{t<l} \hat{u}_{it} < \hat{u}_{it=l}^*$

3. Calculate smoothed search and purchase probabilities using the scaled logistic CDF (Gumbel, 1961) for each draw of q:

   $\Pr_q\left(S_i = \Upsilon \cap y_i = j \,|\, adv_{ij}, \mu_{ij}^p, \sigma_p, p_{ij}, S_i; \theta\right) = \frac{1}{1 + \sum_{m=1}^{M} \exp(-s_m w_{qm})}$

4. Integrate over the distribution of the ϵ_{ij} draws taking the average of the search and purchase probabilities across all Q draws

In the estimation, we use a scaling factor of $s_1 = \ldots = s_M = 5$ and take 100 draws from the error distribution.

Appendix B: Identification of the Sequential Search Model

A. Homogeneous Goods Case

1. Model Set-Up

For homogeneous goods, the sequential search model (with perfect recall) is a pure price search model, i.e. $u_{ij} = -p_{ij}$. Prices follow a market-wide distribution $p \sim D(\mu, \sigma)$ with the probability of getting a below-mean price price draw being λ, i.e. $\Pr(p < \mu) = \lambda$. Consumers have search costs c, make k_i searches and have a reservation price p^*. Let us define the probability of a consumer getting a price draw below the reservation price p^* as q, i.e. $\Pr(p < p^*) = q$. The search rule under sequential search defines that consumers stop searching ***when and only when*** they get a price draw below their reservation price p^*. Finally, let us define event X which takes on the following values: $X_j = 1$ if $p \leq \mu$ and 0 otherwise and $X = \sum_{j=1}^{j=k} X_j$ and event $\tilde{X}$ which takes on the following values: $\tilde{X}_j = 1$ if $p \leq p^*$ and 0 otherwise and $\tilde{X} = \sum_{j=1}^{j=k} \tilde{X}_j$.

2. When Reservation Prices are Observed

If the consumer stops searching after the first search, it must be that $p_1 < p^*$. Thus $\Pr(p_1 < p^* | k = 1) = 1$ and $E\left(\tilde{X}\right) = 1 * \Pr(p_1 < p^* | k = 1) = 1$. Then the expected proportion of below-reservation price p^* prices in consideration sets of size $k = 1$ is $E\left(\frac{\tilde{X}}{k=1}\right) = 1$.

If the consumer stops searching after the second search, it must be that $p_1 > p^*$ and $p_2 < p^*$. Thus $\Pr(p_1 > p^* | k = 2) = 1$ and $\Pr(p_2 < p^* | k = 2) = 1$ and $E\left(\tilde{X}\right) = 1 * \Pr(p_1 > p^* | k = 2) * \Pr(p_2 < p^* | k = 2) = 1$. Then the expected proportion of below-reservation price p^* prices in consideration sets of size $k = 2$ is $E\left(\frac{\tilde{X}}{k=2}\right) = \frac{1}{2}$.

Finally, it is easy to show that, in general, $E\left(\frac{\tilde{X}}{k}\right) = \frac{1}{k}$ and that $E\left(\frac{\tilde{X}}{k}\right)$ decreases as k increases.

3. When Only Expected, but Not Reservation Prices are Observed

When only expected, but not reservation prices are observed, we have to differentiate between two cases: (1) when the reservation price is above the mean of the price distribution and (2) when the reservation price is below the mean of the price distribution. The two cases are presented separately.

Case A: $p* \geq \mu$

Note that the following relation holds in this case: $0 < \lambda < q < 1$.

If the consumer stops searching after the first search, it must be that $p_1 < p^*$. Then $\Pr(p_1 < \mu | p_1 < p^*) = \frac{\lambda}{q}$ and $E(X) = 1 * \Pr(p_1 < \mu | p_1 < p^*) = \frac{\lambda}{q}$. Then the expected proportion of below-mean prices in consideration sets of size $k = 1$ is $E\left(\frac{X}{k=1}\right) = \frac{\lambda}{q}$.

If the consumer stops searching after the second search, the following events are possible:

$X = 0$ $\quad p_1 > p^* \quad \cap \quad \mu < p_2 < p^*$ [informal writing]

$X = 1$ $\quad p_1 > p^* \quad \cap \quad p_2 < \mu < p^*$ [informal writing]

$X = 2$ impossible since both p_1 and p_2 would have to have been smaller than the reservation price and thus the consumer would have never searched a second time

Then $E(X) = 0*\Pr((p_1 > \mu \mid p_1 > p^*) \cap (p_2 > \mu \mid p_2 < p^*)) + 1*\Pr((p_1 > \mu \mid p_1 > p^*) \cap (p_2 < \mu \mid p_2 < p^*)) = 1 * \Pr(p_1 > \mu \mid p_1 > p^*) * \Pr(p_2 < \mu \mid p_2 < p^*) = 1 * 1 * \frac{\lambda}{q} = \frac{\lambda}{q}$ and the expected proportion of below-mean prices in consideration sets of size $k = 2$ is $E\left(\frac{X}{k=2}\right) = \frac{\lambda}{2q}$.

If the consumer stops searching after the third search, the following events are possible [Note that events $X \geq 2$ are impossible via argument above]:

$X = 0$ $\quad p_1 > p^* \quad \cap \quad p_2 > p^* \quad \cap \quad \mu < p_3 < p^*$ [informal writing]

$X = 1$ $\quad p_1 > p^* \quad \cap \quad p_2 > p^* \quad \cap \quad p_3 < \mu < p^*$ [informal writing]

Then $E(X) = 1 * \Pr(p_1 > \mu \mid p_1 > p^*) * \Pr(p_2 > \mu \mid p_2 > p^*) * \Pr(p_3 < \mu \mid p_3 < p^*) = 1 * 1 * 1 * \frac{\lambda}{q} = \frac{\lambda}{q}$ and the expected proportion of below-mean prices in consideration sets of size $k = 3$ is $E\left(\frac{X}{k=3}\right) = \frac{\lambda}{3q}$.

Or, generally, the expected proportion of below-mean prices in consideration sets of size k is $E\left(\frac{X}{k}\right) = \frac{\lambda}{kq}$.

It is easy to show that for any $k > 0$ it is true that $\frac{\lambda}{kq} > \frac{\lambda}{(k+1)q}$. Thus we have shown that the proportion of below-mean prices decreases as consideration sets increase in size for $p^* \geq \mu$.

Case B: $p* < \mu$

Note that the following relation holds in this case: $0 < q < \lambda < 1$.

If the consumer stops searching after the first search, it must be that $p_1 < p^*$. Then $\Pr(p_1 < \mu | p_1 < p^*) = 1 = E(X)$ and the exp. proportion of below-mean prices in consideration sets of size $k = 1$ is $E\left(\frac{X}{k=1}\right) = 1$.

If the consumer stops searching after the second search, the following events are possible:

$X = 0$ impossible since at least one price draw has to be smaller than $p*$. A price draw smaller than p^* is also always smaller than μ.

$X = 1$ $\quad p_1 > \mu > p^* \quad \cap \quad p_2 < p^* < \mu$ [informal writing]

$X = 2$ $\quad p^* < p_1 < \mu \quad \cap \quad p_2 < p^* < \mu$ [informal writing]

Then $E(X) = 1*\Pr(p_1 > \mu | p_1 > p^*) * \Pr(p_2 < \mu | p_2 < p^*) + 2*\Pr(p_1 < \mu | p_1 > p^*) * \Pr(p_2 < \mu | p_2 < p^*) = 1 * \frac{1-\lambda}{1-q} * 1 + 2 * \frac{\lambda - q}{1-q} * 1$. Let us define $a = \frac{1-\lambda}{1-q}$ and $1 - a = \frac{\lambda - q}{1-q}$. Then $E(X) = a + 2(1-a) = 2 - a$ and the expected proportion of below-mean prices in consideration sets of size $k = 2$ is $E\left(\frac{X}{k=2}\right) = \frac{1}{2}(2 - a)$.

If the consumer stops searching after the third search, the following events are possible [$X = 0$ is impossible via argument above]:

$X = 1$	$p_1 > \mu > p^*$	$\cap$	$p_2 > \mu > p^*$	$\cap$	$p_3 < p^* < \mu$	[informal writing]
$X = 2$	$p^* < p_1 < \mu$	$\cap$	$p_2 > \mu > p^*$	$\cap$	$p_3 < p^* < \mu$	[informal writing]
$X = 3$	$p^* < p_1 < \mu$	$\cap$	$p^* < p_2 < \mu$	$\cap$	$p_3 < p^* < \mu$	[informal writing]

Then (skipping the math) $E(X) = 3 - 2a$ and the expected proportion of below-mean prices in consideration sets of size $k = 3$ is $E\left(\frac{X}{k=3}\right) = \frac{1}{3}[3 - 2a]$.

Or, generally, with $a = \left(\frac{1-\lambda}{1-q}\right)$ we can write the exp. proportion of below-mean prices in consideration sets of size k as $E\left[\frac{X}{k}\right] = \frac{1}{k}[k - (k-1)a]$.

Finally, we can show that $E\left[\frac{X}{k}\right] > E\left[\frac{X}{k+1}\right]$:

$\frac{1}{k}[k - (k-1)a] > \frac{1}{k+1}[k + 1 - (k + 1 - 1)a]$

$(k+1)[k - ka + a] > k[k + 1 - ka]$

$k + a > k$

$a > 0$ TRUE since a is a conditional probability

Thus we have shown that the expected proportion of below-mean prices in consideration sets decreases as k increases for $p^* < \mu$.

4. The Proportion of Consumers Searching k Times Decreases As k Increases

Let us first show that the probability that a consumer makes k searches decreases as k increases, i.e. $\Pr(s = k) > \Pr(s = k+1)$:

1. If a consumer stops searching after the first search, it must be that $p_1 < p*$. Since $\Pr(p, < p*) = q$, it must be that $\Pr(p < p*) = q = \Pr(s = 1)$.

2. If a consumer stops searching after the second search, it must be that $p_1 > p*$ and $p_2 < p*$. Since $\Pr(p, < p*) = q$, it must be that $\Pr(s = 2) = (1 - q)q$.

3. It is easy to show that, in general, $\Pr(s = k) = (1 - q)^{k-1} q$.

Suppose there are N consumers. Then the expected proportion of consumers searching k time is $E\left(\frac{\Pr(s=k)N}{N}\right) = (1 - q)^{k-1} q$ since N cancels out. Finally, it is easy to show that $(1 - q)^{k-1} q > (1 - q)^k q$. Thus we have shown that the proportion of consumers searching k times decreases as k increases.

B. Differentiated Goods

1. Model Set-Up

The following set-up is directly taken from Weitzman (1979): Consumers receive utility from buying a good from company j and have a full utility specification such as $u_{ij} = \alpha_j + \beta X_{ij} + \gamma p_j + \epsilon_{ij}$ with $\gamma < 0$ and

$\epsilon_{ij} \sim iid$ with $\mu^{\epsilon} = 0$. As for homogeneous goods, this is a sequential search model with recall. Prices follow some company-specific distributions $p_j \sim D_j(\mu_j, \sigma_j)$ with the probability of getting a below-mean price price draw being $\Pr(p < \mu_j) = \lambda$. Consumers have search costs c_{ij} and make k_i searches.

Given the assumptions for the price distributions, consumers' utility function has the following distribution (from the consumer's perspective):

$$u_{ij} \sim N(\alpha_j + \beta X_{ij} + \gamma \mu_j + \epsilon_{ij}; \gamma \sigma_j)$$

or, short, $u_{ij} \sim N(\mu_{ij}^u, \sigma_j^u)$. Further, since $\Pr(p < \mu_j) = \lambda$, it must be that $\Pr(u > \mu_{ij}^u) = \lambda$, i.e. a below-mean price price draw always results in an above-mean utility utility.

Next, let us define u_{ij}^* as the consumer's reservation utility, i.e. the utility that makes the consumer indifferent between stopping and continuing to search. Using Weitzman's (1979) selection rule, we know that the consumer orders all alternatives in a decreasing order of their reservation utilities. The consumer first searches the alternative with the highest, then the alternative with the second highest etc. reservation utility. To express the ranking according to the reservation utilities u_{ij}^*, let us define $u_{i,t=1}^*$ be the company with the highest reservation utility for consumer i, $u_{i,t=2}^*$ the company with the second-highest reservation utility for consumer i etc.

Using Weitzman's (1979) stopping rule which says that the consumer stops searching when the maximum utility among the searched alternatives is larger than the maximum reservation utility among the non-searched companies, we define $\Pr\left(\max\limits_{t \in S_i} \quad u_{it} > u_{i,t+1}^*\right) = q_{it}$, i.e. the probability that the condition that the maximum utility among the searched companies is larger than the maximum reservation utility among the non-searched companies is going to the satisfied in the t^{th} search is q_{it}. Since $\max\limits_{t \in S_i} \quad u_{it}$ can only stay constant or increase as the consumer searches more and the maximum reservation utility among the non-searched companies $u_{i,t+1}^*$ can only stay constant or decrease as the consumer searches more, it is easy to show that $q_1 < q_2 < \ldots < q_J$.

Finally, let us define event X which takes on the following values: $X_j = 1$ if $\max\limits_{t \in S_i} u_{it} > \mu_{ij}^u$ and 0 otherwise and $X = \sum_{j=1}^{j=k} X_j$ and event $\tilde{X}$ which takes on the following values: $\tilde{X}_j = 1$ if $\max\limits_{t \in S_i} u_{it} > u_{ij}^*$ and 0 otherwise and $\tilde{X} = \sum_{j=1}^{j=k} \tilde{X}_j$.

Note that, in the following, we leave the subscript i out. Since we can show that the patterns hold for every individual consumer i, they must also hold for all consumers.

2. When Reservation Utilities are Observed

If the consumer stops searching after the first search, it must be that $u_1 > u_2^*$. Thus $\Pr(u_1 > u_2^* | k = 1) = 1$ and $E\left[\tilde{X}\right] = E\left[\frac{\tilde{X}}{k=1}\right] = 1$.

If the consumer stops searching after the second search, it must be that $u_1 < u_2^*$ and $\max(u_1, u_2) > u_3^*$. Then $\Pr(u_1 < u_2^* | k = 2) = 1$ and $\Pr(\max(u_1, u_2) > u_3^* | k = 2) = 1$. Thus $E\left[\tilde{X}\right] = 1$ and $E\left[\frac{\tilde{X}}{k=2}\right] = \frac{1}{2}$.

It is easy to show that, in general, $E\left[\frac{\tilde{X}}{k}\right] = \frac{1}{k}$ and that $E\left[\frac{\tilde{X}}{k}\right]$ decreases as k increases.

3. When Only Expected Prices, but not Researvation Utilities are Observed

Case A: $\max\limits_{t \notin S} u_t^* \leq \mu^u$

If the consumer stops searching after the first search, it must be that $u_1 > u_2^*$. Then $\Pr(u_1 > \mu^u | u_1 > u_2^*) = \frac{\lambda}{q_1}$. Thus $E[X] = E\left[\frac{X}{k=1}\right] = \frac{\lambda}{q_1}$.

If the consumer stops searching after the second search, it must be that $u_1 < u_2^*$ and $\max(u_1, u_2) > u_3^*$.

$X = 0$	$u_1 < u_2^* < \mu^u \quad \cap \quad u_3^* < \max(u_1, u_2) < \mu^u$	[informal writing]
$X = 1$	$u_1 < u_2^* < \mu^u \quad \cap \quad u_3^* < \mu^u < \max(u_1, u_2)$	[informal writing]
$X = 2$	impossible since then both u_1 and u_2 would have to have been larger than their mean utilities. Since $\max\limits_{t \notin S} u_t^* < \mu^u$ this also means that u_1 would have to have been larger than u_2^* and the consumer would have never made a second search.	

Then $E[X] = 1 * \Pr(u_1 < \mu^u | u_1 < u_2^*) * \Pr(\max(u_1, u_2) > \mu^u | \max(u_1, u_2) > u_3^*) = 1 * 1 * \frac{\lambda}{q_2} = \frac{\lambda}{q_2}$ and the expected proportion of below-mean prices in consideration sets of size $k = 2$ is $E\left[\frac{X}{k=2}\right] = \frac{\lambda}{2q_2}$.

Or, generally, the expected proportion of below-mean prices in consideration sets of size k is $E\left[\frac{X}{k}\right] = \frac{\lambda}{kq_k}$. Since $q_k < q_{k+1}$, it is easy to show that for any $k > 0$ it is true that $\frac{\lambda}{kq_k} > \frac{\lambda}{(k+1)q_{k+1}}$. Thus we have shown that the exp. proportion of below-mean prices decreases as consideration sets increase in size for $\max\limits_{t \in S} u_t \leq \mu^u$.

Case B: $\max\limits_{t \notin S} u_t^* > \mu^u$

If the consumer stops searching after the first search, it must be that $u_1 > u_2^*$. Then $\Pr(u_1 > \mu^u | u_1 > u_2^*) = 1$ and $E[X] = E\left[\frac{X}{k=1}\right] = 1$.

If the consumer stops searching after the second search, the following events are possible:

$X = 0$	impossible since a consumer does not stop searching until he gets at least one utility draw above his $\max\limits_{t \notin S} u_t^*$. Since $\max\limits_{t \notin S} u_t^* > \mu^u$, a utility draw larger than $\max\limits_{t \notin S} u_t^*$ is also always larger than μ^u.	
$X = 1$	$u_1 < \mu^u < u_2^* \quad \cap \quad \{u_2 > \mu^u \cap \max(u_1, u_2) > u_3^*\}$	[informal writing]
$X = 2$	$\mu^u < u_1 < u_2^* \quad \cap \quad \{u_2 > \mu^u \cap \max(u_1, u_2) > u_3^*\}$	[informal writing]

Then $E[X] = \Pr(u_1 < \mu^u | u_1 < u_2^*) \Pr(u_2 > \mu^u | \max(u_1, u_2) > u_3^*)$

$+2 * \Pr(u_1 > \mu^u | u_1 < u_2^*) \Pr(u_2 > \mu^u | \max(u_1, u_2) > u_3^*) = \frac{1-\lambda}{1-q_1} + 2\frac{\lambda - q_1}{1-q_1}$. Let us define $a_k = \frac{1-\lambda}{1-q_1}$ and $1 - a_k = \frac{\lambda - q}{1-q_1}$. Then $E[X] = a_1 + 2(1 - a_1) = 2 - a_1$ and the exp. proportion of below-mean prices in consideration sets of size $k = 2$ is $E\left[\frac{X}{k=2}\right] = \frac{1}{2}(2 - a_1)$.

If the consumer stops searching after the third search, the following events are possible [$X = 0$ impossible via argument above]:

$X = 1 \quad u_1 < \mu^u < u_2^* \quad \cap \quad \{u_2 < \mu^u \cap \max(u_1, u_2) < u_3^*\} \quad \cap \quad \{u_3 > \mu^u \cap \max(u_1, u_2, u_3) > u_4^*\}$

$X = 2 \quad \mu^u < u_1 < u_2^* \quad \cap \quad \{u_2 < \mu^u \cap \max(u_1, u_2) < u_3^*\} \quad \cap \quad \{u_3 > \mu^u \cap \max(u_1, u_2, u_3) > u_4^*\}$

$X = 2 \quad u_1 < \mu^u < u_2^* \quad \cap \quad \{u_2 > \mu^u \cap \max(u_1, u_2) < u_3^*\} \quad \cap \quad \{u_3 > \mu^u \cap \max(u_1, u_2, u_3) > u_4^*\}$

$X = 3 \quad \mu^u < u_1 < u_2^* \quad \cap \quad \{u_2 > \mu^u \cap \max(u_1, u_2) < u_3^*\} \quad \cap \quad \{u_3 > \mu^u \cap \max(u_1, u_2, u_3) > u_4^*\}$

Then (skipping the math) $E[X] = 3 - a_1 - a_2$ with $a_k = \left(\frac{1-\lambda}{1-q_k}\right)$ and $1 - a_k = \left(\frac{\lambda - q_k}{1-q_k}\right)$ and the exp. proportion of below-mean prices in consideration sets of size $k = 3$ is $E\left[\frac{X}{k=3}\right] = \frac{1}{3}(3 - a_1 - a_2)$.

Or generally, with $a_k = \left(\frac{1-\lambda}{1-q_k}\right)$ and $1 - a_k = \left(\frac{\lambda - q_k}{1-q_k}\right)$ the exp. proportion of below-mean prices in consideration sets of size k is $E\left[\frac{X}{k}\right] = \frac{1}{k}\left(k - \sum_{i=1}^{k-1} a_i\right)$.

Finally, we can show that $E\left[\frac{X}{k}\right] > E\left[\frac{X}{k+1}\right]$:

$\frac{1}{k}\left(k - \sum_{i=1}^{k-1} a_i\right) > \frac{1}{k+1}\left(k + 1 - \sum_{i=1}^{k} a_i\right)$

$(k+1)\left(k - \sum_{i=1}^{k-1} a_i\right) > k\left(k + 1 - \sum_{i=1}^{k} a_i\right)$

$-k\sum_{i=1}^{k-1} a_i - \sum_{i=1}^{k-1} a_i > -k\sum_{i=1}^{k} a_i$

$\sum_{i=1}^{k-1} a_i < k a_k \qquad$ TRUE since $a_1 < a_2 < \ldots < a_J$

Thus we have shown that the exp. proportion of below-mean prices in consideration sets decreases as k increases for $\max_{t \notin S} u_t^* > \mu^u$.

4. The Proportion of Consumers Searching k Times Decreases As k Increases

1. If consumer i stops searching after the first search, it must be that $u_{i,t=1} > u_{i,t=2}^*$. The probability of this event is $\Pr\left(u_{i,t=1} > u_{i,t=2}^*\right) = \Pr(s = 1) = q_{i1}$.

2. If consumer i stops searching after the second search, it must be that $u_{i,t=1} < u_{i,t=2}^*$ and $\max(u_{i,t=1}, u_{i,t=2}) > u_{i,t=3}^*$. The probability of this event is $\Pr(s = 2) = (1 - q_{i1}) q_{i2}$

3. It is easy to show that, in general, $\Pr(s = k) = \prod_{m=1}^{m=k-1} (1 - q_{im}) q_{ik}$.

For consumer i for the probability of searching k times to decrease as k increases, the following condition must hold:

$$\prod_{m=1}^{m=k-1} (1 - q_{im}) q_{ik} > \prod_{m=1}^{m=k} (1 - q_{im}) q_{i,k+1}$$

The above condition holds *if and only if*

$$\frac{q_{ik}}{1-q_{ik}} > q_{i,k+1}$$

The expected proportion of consumers searching k times is $\frac{1}{N}\sum_i \Pr(s=k) = \frac{1}{N}\sum_i \prod_{m=1}^{m=k-1}(1-q_{im})\, q_{ik}$. Then to show that the proportion is decreasing as k increases, the following condition has to hold:

$$\frac{1}{N}\sum_i \prod_{m=1}^{m=k-1}(1-q_{im})\, q_{ik} > \frac{1}{N}\sum_i \prod_{m=1}^{m=k}(1-q_{im})\, q_{i,k+1}$$

Appendix C: Demographic Factors

In the utility function, we include two types of demographic factors: two psychographic factors, namely, "attitude towards auto insurance shopping and switching" and "new technology adoption" and two factors describing observed brand preferences, namely, "proven reliability" and "out-of-box character." We recovered both types of factors using two separate factor analyses.

The upper part of Table 21 shows the content of the items (questions) that constitute the two psychographic factors as well as descriptive statistics for them. The questions were measured on a scale from 1 to 5 where 1 indicates "completely disagree," 3 indicates "neither disagree nor agree" and 5 indicates "completely agree." The standard deviations ranging from .91 to 1.03 on a 5-point scale indicate considerable variation in psychographics across consumers.

The lower part of Table 21 displays the content of the items (questions) that constitute the two observed brand preferences and their descriptive statistics. The items were measured on a scale from 1 to 7. The standard deviations range from 1.27 to 1.41 on a 7-point scale and indicate considerable variation in attitudes across consumers.

Please indicate your agreement with each of the following statements regarding...	**Mean**	**Std. Dev.**	**Factor**
...your shopping habits.			
I am always one of the first of my friends to try new products or services.	2.7658	.9560	B
...your brand loyalty and technology.			
I enjoy reading about new technology products.	3.3927	.9663	B
I am among the first of my friends and colleagues to try new technology products.	2.9088	1.0306	B
...auto insurance.			
Switching to another auto insurer is not worth the risk.	2.3472	.9125	A
Shopping for a new auto insurer is too difficult or time consuming.	2.3865	.9328	A
I have invested too much time into building a relationship with my current agent or insurer to switch to a new auto insurer.	2.3057	.9784	A
Please take a look at the pairs of statements below and select the box closest to the statement that you think best describes the auto insurer.	**Mean**	**Std. Dev.**	**Factor**
Conventional (1) vs. Innovative (7)	4.1799	1.4125	D
Unproven (1) vs. Trusted (7)	5.1565	1.3679	C
Slow (1) vs. Responsive (7)	4.9439	1.3976	C
Careless (1) vs. Protective (7)	4.8967	1.2675	C
Volatile (1) vs. Stable (7)	5.1466	1.3200	C
Serious (1) vs. Fun (7)	3.8677	1.3472	D

Table 21: Descriptive Statistics
A: Attitude towards Auto Insurance Shopping & Switching
B: New Technology Adoption
C: Proven Reliability
D: Out-of-the-Box Character

Appendix D: Sequential Search Model Estimation Approach for Auto Insurance Data

We present a general estimation approach for the sequential search model in Section 4.2 of the paper. To estimate the sequential search model with insurance data, we need to adapt our estimation approach. The reason for this adaptation is the industry practice to send consumers a "free" renewal offer. "Free" in this context means that the consumer does not incur any (search) cost to learn the exact price he would have to pay to renew his insurance policy with his previous insurance provider. We incorporate this industry practice in our model by assuming that consumers receive the renewal notice before starting their search and therefore know the price their previous insurance provider is going to charge them to renew the insurance policy beforehand.

Let us define $u_{ij_{PI}}$ as the utility a consumer receives from their previous insurer's renewal offer and C_i as consumer $i's$ consideration set of size $k+1$ containing his previous insurer and the set of companies he searched. Equation (13) can remain as it is. We then need to adapt equations (14) - (18) from the paper:

First, to reflect the choice and stopping rules, the maximum utility among the searched companies and the renewal offer from the previous insurer have to be larger than any other utility among the considered companies and the maximum reservation utility among the non-considered companies, i.e.

$$\max_{j \in C_i} u_{ij} \;\geq\; u_{ij'}, \max_{j'' \notin S_i} u^*_{ij''} \qquad \forall j' \in C_i \setminus \{j\} \tag{21}$$

Second, the equations illustrating why it must have been optimal for the consumer not to stop searching and purchase earlier given Weitzman's (1979) rules (equations (15) - (17) in the paper) also must be adapted. Recall that, in the estimation, given a set of estimates for the unknown parameters, for each consumer i, we rank all searched companies j according to their reservation utilities $\hat{u}^*_{it}$ (the "^" symbol refers to quantities computed at the current set of estimates) where $t = 1, ..., k$ indicates the rank of a consumer's reservation utility among the searched companies. Note that $t = 1$ ($t = k$) denotes the company with the largest (smallest) reservation utility $\hat{u}^*_{it}$ among the searched companies. Further rank all utilities of searched companies in the same order as the reservation utilities, i.e. $\hat{u}_{i,t=1}$ denotes the *utility* for the company with the highest *reservation* utility $\hat{u}^*_{it}$. If a consumer considered two companies (i.e. the previous insurer and another company), the utility from the renewal offer by the previous insurer must have been smaller than the reservation utility from the other considered company thereby prompting the consumer to search after receiving the renewal offer, i.e.

$$\hat{u}_{ij_{PI}} < \hat{u}^*_{i,t=1} \tag{22}$$

Similarly, if a consumer considered three companies, the following conditions must hold

$$\hat{u}_{ij_{PI}} < \hat{u}^*_{it=1} \quad \cap \quad \max \left(\hat{u}_{ij_{PI}}, \hat{u}_{i,t=1}\right) < \hat{u}^*_{i,t=2} \tag{23}$$

or generally

$$\bigcap_{l=2}^{k+1} \max_{t<l-1} \left(\hat{u}_{ij_{PI}}, \hat{u}^*_{it}\right) < \hat{u}^*_{it=l-1} \tag{24}$$

Given equations (13),(14) and (18) the probability of observing a consumer search a set of companies Υ and purchase from company j under sequential search is given by

$$\Pr\left(S_i = \Upsilon \cap y_i = j \,|\, adv_{ij}, \mu^p_{ij}, \sigma_p, p_{ij}, S_i; \theta\right)$$

$$= \Pr \quad (\quad \min_{j \in S_i} u^*_{ij} \geq \max_{j' \notin S_i} u^*_{ij'} \quad \cap \quad \max_{j \in C_i} u_{ij} \geq u_{ij'}, \max_{j'' \notin S_i} u^*_{ij''}$$

$$\bigcap_{l=2}^{k+1} \max_{t<l-1} \left(\hat{u}_{ij_{PI}}, \hat{u}^*_{it}\right) < \hat{u}^*_{it=l-1} \qquad \forall j' \in C_i \setminus \{j\},\ t = 2, \ldots, k \quad) \tag{25}$$

and the loglikelihood of the model is shown in equation (19). As in the simulation studies, we use the approach suggested by Kim et al. (2010) to calculate consumers' reservation utilities and SMLE to estimate the model.