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

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Abstract

We show that the search method consumers use when resolving uncertainty in the prices of alternatives is identified in data where consumers' consideration sets (but not sequence of searches), prices for the considered alternatives and market-wide price distributions are observed. The search method is non-parametrically identified by different patterns of actual prices in consumers' consideration sets across search methods. We also provide a new estimation approach for the sequential search model; complementing earlier work that has estimated a simultaneous search model with such data. Using a novel data set on consumer shopping behavior in the U.S. auto insurance industry that contains information on consideration sets and choices, we find that the pattern of actual prices in consumers' consideration sets are consistent with consumers searching simultaneously. Our counterfactuals show that the largest insurance companies are better off in terms of market share when consumers search sequentially, while smaller companies benefit from consumers searching simultaneously. The results regarding the composition of the customer base are mixed. As the search method affects consumers' consideration sets, which in turn influence brand choices, understanding the nature of consumer search and its implications for consideration and choice is important from a managerial perspective.

Keywords: consumer search, simultaneous search, sequential search, auto insurance industry

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1 Introduction

Understanding the formation of consideration sets and their subsequent implications for consumers' product choices has long been an area of interest to marketers (e.g., Hauser and Wernerfelt 1990). Accordingly, researchers have tried to understand how these sets are formed (Hauser and Wernerfelt 1990) or have tried to account for them when studying choice behavior (Siddharth et al. 1995, Chiang et al. 1999, Mehta et al. 2003, Seiler 2013). In the latter case, even in the absence of data on consideration sets, researchers have tried to incorporate the notion of consideration sets via functional form assumptions on consideration set and choice probabilities. Explicitly accounting for the role of consideration sets in choice is important from the perspective of correctly measuring consumers' brand preferences and their sensitivities to marketing activities as failure to do so could lead to incorrect inferences regarding these market fundamentals. At the same time, research in economics has shown that the process by which a consumer arrives at his or her consideration set also has implications for these parameters and consequently for firms operating in the market.

The theoretical underpinnings of consideration set formation are in the models of search. 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 consideration set 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.[1]

As the search method consumers use has implications for whether or not a firm's brand is included in the consideration set, a pertinent question is: Do some companies benefit from consumers using a specific search method?[2] If the answer is yes, then companies have a reason to try to influence consumers' search strategies. In this paper, we look at situations in which consumers are uncertain about price (but not the other attributes of the product) and study two search methods that help

[1]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.

[2]We evaluate whether companies benefit from a specific search method by looking at market shares and the composition of a company's customer base.

them resolve this uncertainty, namely, simultaneous and sequential search. Under a 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 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).

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 (2013), and Muir et al. (2013) assume that consumers search simultaneously, while Dahlby and West (1986), Kim et al. (2010), and Mojir et al. (2014) assume that consumers search sequentially. In this paper, we focus on the case where consumers engage in price search and the researcher observes each consumer's consideration set (but not the sequence of searches), besides purchase outcomes, prices, price distributions and other characteristics. We show that, under certain assumptions, the search method is indeed identified by the price patterns in consumers' observed consideration sets. Differences in price patterns emerge because in simultaneous search consumers only use information on the expected prices to decide which and how many companies to search, whereas in sequential search consumers continue searching and consider more alternatives only when they receive high price draws for the initially considered alternatives. Our identification strategy holds for a broad range of settings that we discuss in detail in the Identification section.

Next, we examine the consequences of imposing an incorrect search method assumption on the estimated consumer preference and search cost parameters 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 (2014), we propose an SMLE-based approach for the sequential search model. Using extensive simulations we are able to show that incorrect assumptions on the search method could lead to different consideration sets and biased estimates of preference parameters and search costs.

We then provide an empirical application of our search method identification strategy and new sequential search estimation approach. Using data on consumers' consideration sets, purchases, prices and other characteristics we first ask: do households search simultaneously or sequentially when shopping for auto insurance price quotes? Since consumers in our sample have previously been insured and coverage levels tend not to change much, assuming that consumers engage in price search is a reasonable assumption in this context. We look for model-free evidence of 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 simultaneous search. Our search costs estimate is of $42. We then study via counterfactuals whether some companies win or lose when consumers change their search method and how their customer bases are affected as a consequence. We find that the largest insurance companies are better off in terms of market shares when consumers search sequentially, while smaller companies profit from consumers searching simultaneously. We then assess the robustness of our results to the presence of unobserved heterogeneity in the search method and in the preference parameters and to assumptions required by our estimation methods.

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. Second, we provide a comparison of the consequences of assuming simultaneous versus sequential search strategies on the parameter estimates 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 (2014) provides an approach for simultaneous search that we adopt here, we propose an estimation approach under the sequential search assumption. Fourth, we provide extensive simulations to show that our estimation methods can recover true model parameters. Importantly, 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. And finally, we quantify the effects of consumers changing their search method and its implications for firms in the auto insurance market.

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. In section 7, we discuss our empirical application and in section 8 we study several counterfactuals. In section 9, we check the robustness of our results. 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. As this literature is extensive, we only focus on recent efforts to structurally estimate search models or to identify the search method from data. De los Santos et al. (2012) show that with data on purchases, consideration sets and the sequence of searches the search method consumers use is identified for both homogeneous and differentiated goods. In this paper, we focus on the situation where the researcher only observes consideration sets and purchases, but not the sequence of searches, i.e. the researcher has less information, and show that even in this case the search method is identified. Hong and Shum (2006) develop methodologies to estimate search costs under both simultaneous and sequential search when only prices are observed. In this paper, we are able to relax several of Hong and Shum's (2006) assumptions: For example, we allow goods to be differentiated and price distributions to be company-specific. 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 which allow them to test between simultaneous and sequential search models. Chen et al. (2007) do not find significant differences between the simultaneous and sequential search models using the usual significance levels in their empirical application. Finally, this paper is also related to Honka (2014). 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 (2014) uses. While she assumes that all consumers search simultaneously, we show that her assumption is appropriate.

3 Model

We present a general differentiated goods price search model that can be used for markets with any number of alternatives. 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

$$u_{ij} = \alpha_j + \beta p_{ij} + X_{ij}\gamma + \epsilon_{ij} \tag{1}$$

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_j^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. X_{ij} may contain other variables that influence consumer utility. These variables can be consumer-specific (e.g. demographics), company-specific (e.g. advertising spending) or both. α_j, β, γ are parameters to be estimated.

Our goal is to present simultaneous and sequential search models and estimation approaches that can be used for markets with any number of alternatives. This is a challenge for the estimation of a simultaneous search model which suffers from the curse of dimensionality (Chiang et al. 1999, Kim et al. 2010). To overcome this challenge, we use the theory developed by Chade and Smith (2005). Their theory can only be used under two conditions: (1) first-order stochastic dominance among the price distributions and (2) search costs cannot be company-specific. We implement the first condition by assuming that the variances of the price distributions are identical.[3] Note that

[3] We study the effects of the equal price variance and identical search costs assumptions for both the simultaneous and sequential

these two assumptions are not necessary for the sequential search model, but that we nevertheless make them to keep everything other than the search method consistent across the simultaneous and sequential search model. Further, our identification results do not rely on these two assumption as described in Section 5.1.

3.1 Simultaneous Search

The simultaneous search model we present in this section is closely related to the one developed in Honka (2014). The main difference between the two models is that Honka (2014) assumes that prices follow an EV Type I distribution, while we assume that prices follow a normal distribution. This change in distributional assumption is driven by the desire to have the same distributional assumption on prices under both simultaneous and sequential search.[4] Given the normal assumption for prices, the utility u_{ij} is a normally distributed random variable with mean $\mu_{ij} = \alpha_j + \beta\mu_j^p + X_{ij}\gamma + \epsilon_{ij}$ and standard deviation $\sigma = \beta\sigma_p$. 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

$$E\left[u_{ij}\right] = \alpha_j + \beta E\left[p_j\right] + X_{ij}\gamma + \epsilon_{ij} \tag{2}$$

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. O_{ik} denotes the set of top k companies consumer i ranked highest according to their EIU. For example, O_{i1} contains the company with the highest expected utility for consumer i, O_{i2} contains the companies with the two highest expected utilities for consumer i, etc. 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*, i.e. if there are J companies in the market, the consumer can choose among N choice sets. A consumer's benefit of a searched *set* S_i is given by the expected *maximum* utility among the searched brands. The consumer picks the size of his searched set S_i which maximizes his net benefit of searching denoted by Γ_{ik}, i.e. expected maximum utility among the searched companies minus the cost of search

search model in simulation studies in Appendix E.

[4] 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.

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

As standard in the search literature, we assume that the first search is free to ensure that all consumers search at least once.[5] 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. Given the assumed normal distribution prices, there is no closed-form solution for the expected maximum utility $E\left[\max_{j \in O_{ik}} u_{ij}\right]$. We 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.

$$j = \arg\max_{j \in S_i} u_{ij} \tag{4}$$

where u_{ij} now includes the quoted prices for consumer i by company j.

3.2 Sequential Search

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

$$c = \int_{r_{ij}}^{\infty} (u_{ij} - r_{ij})\, f(u_{ij})\, du_{ij} \tag{5}$$

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.

$$\max_{j \in S_i} u_{ij} > \max_{j' \notin S_i} r_{ij'} \tag{6}$$

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.

[5] 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: First, while the consumer knows the distributions of prices in the market, the researcher does not. Second, 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. And third, in contrast to the consumer, the researcher does not observe ϵ_{ij}. To address the first issue that 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 (2014) 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'.

We account for the fact that the researcher does not observe ϵ_{ij} by assuming that ϵ_{ij} 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 given by

$$P_{i\Upsilon|\epsilon} = P\left(\min_{j \in S_i} \left(E\left[u_{ij}\right]\right) \geq \max_{j' \notin S_i} \left(E\left[u_{ij'}\right]\right) \quad \cap \quad \Gamma_{ik} \geq \Gamma_{ik'} \qquad \forall k \neq k'\right) \tag{9}$$

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

$$P_{ij|\Upsilon,\epsilon} = P\left(u_{ij} \geq u_{ij'} \quad \forall j \neq j', \quad j, j' \in S_i\right) \tag{10}$$

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.

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 purchase probabilities given by (10). We maximize the joint likelihood of consideration set and purchase. The likelihood of our model is given by

$$L = \prod_{i=1}^{N} \int_{-\infty}^{+\infty} \left(\prod_{l=1}^{L} \prod_{j=1}^{J} P_{i\Upsilon|\epsilon}^{\vartheta_{il}} P_{ij|\Upsilon,\epsilon}^{\delta_{ij}} \right) f(\epsilon)\, d\epsilon \tag{11}$$

where ϑ_{il} indicates the chosen consideration set and δ_{ij} the company from which insurance is purchased. Neither the consideration set nor the conditional purchase probability have a closed-form solution. Honka (2014) 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 net benefit of a searched set Γ_{ik}, 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 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.[6] 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 scaling parameters $s_1 = ... = s_M = 5$. Fourth, we average the smoothed consideration and conditional purchase probabilities across all ϵ_{ij} draws. In the estimation, we set D to 200 and Q to 100.

4.2 Sequential Search

Since we do not observe the sequence of searches, 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.

[6]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.

$$\min_{j \in S_i} r_{ij} \geq \max_{j' \notin S_i} r_{ij'} \tag{12}$$

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

$$\max_{j \in S_i} u_{ij} \geq u_{ij'}, \max_{j'' \notin S_i} r_{ij''} \qquad \forall j' \in S_i \setminus \{j\} \tag{13}$$

i.e. that 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 (12) and (13) 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.

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 $\hat{r}_{it}$ (the "ˆ" 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 $\hat{r}_{it}$. 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 $\hat{r}_{it=1}$. Then *given the current parameter estimates* the following conditions have to hold

$$\hat{u}_{i,t=1} < \ \hat{r}_{it=2} \quad \cap \quad \max_{t=1,2} \hat{u}_{it} < \hat{r}_{i,t=3} \tag{14}$$

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 do a second search. Similarly, the maximum utility from the (predicted) first and second search has to be smaller than the reservation utility from the (predicted) third search; otherwise the consumer would not have searched a third time. Generally, for a consumer searching $t = 2, \ldots, k$ companies, the following set of conditions has to hold

$$\bigcap_{l=2}^{k} \max_{t<l} \hat{u}_{it} \ < \ \hat{r}_{it=l} \tag{15}$$

To calculate a consumer's reservation utilities, we follow the approach suggested by Kim et al. (2010). The additional estimation conditions as described in equation (15) are necessary to correctly recover search costs. These conditions impose restrictions on the utilities and bound the search cost parameter from above. Without these conditions, search cost estimate is 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

$$P_{ij\Upsilon|\epsilon} = P(\min_{j \in S_i} r_{ij} \geq \max_{j' \notin S_i} r_{ij'} \ \cap \ \max_{j \in S_i} u_{ij} \geq u_{ij''}, \max_{j' \notin S_i} r_{ij'} \ \cap \ \bigcap_{l=2}^{k} \max_{t<l} \hat{u}_{it} < \hat{r}_{it=l} \quad \forall j'' \in S_i \backslash \{j\}, t = 2, \ldots, k) \tag{16}$$

Then the loglikelihood of the model is given by

$$L = \prod_{i=1}^{N} \int_{-\infty}^{+\infty} \prod_{l=1}^{L} \prod_{j=1}^{J} P_{ij\Upsilon|\epsilon}^{y_{il}} f(\epsilon) \, d\epsilon \tag{17}$$

where y_{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 (16) 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 (16) 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 (16) 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 (16) without having to write out all admissable rankings.

As in the estimation of 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 in data where consideration sets and actual prices are observed. Next, we describe the identification of the model parameters conditional on a search method. Our discussion of identification rests on the assumption that consumers know the distribution of prices and that prices are the only source of uncertainty for the consumer which he is resolving through search. As is common in the literature on consumer search, 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 first discuss the price patterns we would observe under simultaneous and sequential search and then describe circumstances under which these patterns are distinct and those under which they are not; the latter provides conditions under which the search method is not identified.

We start out by discussing the data pattern that characterizes the simultaneous search method. Recall that prices follow some (potentially company-specific) distributions. Let us define $\Pr(p_j \leq \mu_j) = \lambda$, i.e. the probability that a price draw is below the expected price is λ. Further we define event $X = 1$ as a below-price expectation price draw and $X = 0$ as an above-price expectation 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-price expectation prices in a consumer's consideration set of size k as

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

Thus we expect λ percent of the price draws in consumers' consideration sets to be above above and $(1-\lambda)$ percent 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 that prices follow normal distributions in the empirical sections of this paper, 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 percent of the price draws to be below and 50 percent of the price draws to be above the price means.

This identification strategy for the simultaneous search method holds 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 that the identification strategy for the simultaneous search method holds 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 is characteristic for this search method. We present here the proof for differentiated goods and refer the reader to Appendix B for a detailed analytical proof for both homogeneous and differentiated goods.

The following set-up is taken from Weitzman (1979): Consumers have a some utility function such as $u_{ij} = \alpha_j + \beta p_{ij} + X_{ij}\gamma + \epsilon_{ij}$ with $\beta < 0$ and $\epsilon_{ij} \sim iid$ with $\mu^{\epsilon} = 0$. This is a sequential search model with recall. Prices follow some company-specific distributions $p \sim D_j\left(\mu_j^p, \sigma_j^p\right)$ with the probability of getting a below-price expectation price draw being λ, i.e. $P\left(p < \mu_j^p\right) = \lambda$. Consumers have search costs c_{ij} and make k_i searches. Consumers have reservation prices r_{ij}. Given the assumptions for the price distributions, consumers' utility function also follows distribution D_j, i.e. $u_{ij} \sim D_j\left(\mu_{ij}, \sigma_j\right)$ with $\mu_{ij} = \alpha_j + \beta\mu_j^p + X_{ij}\gamma + \epsilon_{ij}$ and $\sigma_j = \gamma\sigma_j^p$. Further, since $P\left(p < \mu_j^p\right) = \lambda$, it must be that $P\left(u > \mu_{ij}\right) = \lambda$, i.e. a below-price expectation price draw always results in an above-mean utility utility.

Using Weitzman's (1979) selection rule, we know that consumers order all alternatives in a decreasing order of their reservation utilities r_{ij}. Consumers first search the alternative with the highest, then the alternative with the second highest etc. reservation utility. To express the ranking according to the reservation utilities r_{ij}, let us define $r_{i,t=1}$ as the company with the highest reservation utility for consumer i, $r_{i,t=2}$ as the company with the second-highest reservation utility for consumer i etc. Using Weitzman's (1979) stopping rule, we know that consumers stop searching when the maximum utility among the searched alternatives is larger than the maximum reservation utility among the non-searched companies.

Before the 1st search we can differentiate between two types of consumers - type A and type B - with $N = N^{b1,A} + N^{b1,B}$. For type A consumers, the reservation utility of the potentially second-to-be-searched company is smaller than the expected utility of the company searched first, i.e. $r_{i,t=2} < \mu_{i,t=1}$, and for type B consumers, the reservation utility of the potentially second-to-be-searched company is larger than the expected utility of the company searched first, i.e. $r_{i,t=2} \geq \mu_{i,t=1}$. Note that consumers can change their type, i.e. change from being type B to being type A consumers (but not vice versa!) during the search process. Therefore $''b1"$ in $N^{b1,A}$ and $N^{b1,B}$ stands for the number of consumers belonging to type A and type B, respectively, before the 1st search.

Before the 1st search there are N consumers ready to search.[7] Since prices are randomly and independently drawn, $\lambda\left(N^{b1,A} + N^{b1,B}\right)$ consumers get a utility draw that is above the expected utility of the company searched first (due to a below-price expectation price draw) and $(1-\lambda)\left(N^{b1,A} + N^{b1,B}\right)$ consumers get a utility draw that is below the expected utility of the company searched first (due to an above-price expectation price draw): All type A consumers who got a utility draw that is above the expected utility of the company searched first, stop searching after the 1st search since any utility draw that is above the expected utility of the company searched first is always larger than the reservation utility of the potentially second-to-be-searched company $r_{i,t=2}$. Among the type B consumers who got a utility draw that is above the expected utility of the company searched first, a proportion

[7]Without loss of generality we assume that all consumers search at least once.

$0 \leq \delta_1 \leq 1$ stops searching since their utility draws were larger than the reservation utilities of the potentially second-to-be-searched companies $r_{i,t=2}$ and a proportion $(1-\delta_1)$ continues to search since their utility draws were below the reservation prices of the potentially second-to-be-searched companies. Now, let us turn to the consumers who got a utility draw that is below the expected utility of the company searched first (due to an above-price expectation price draw): Among the type A consumers who got a utility draw that is below the expected utility of the company searched first, a proportion $0 \leq \gamma_1 \leq 1$ stops searching since the utility draws were larger than the reservation utilities of the potentially second-to-be-searched company $r_{i,t=2}$ and a proportion $(1-\gamma_1)$ continues to search since their utility draws were below the reservation utilities of the potentially second-to-be-searched company. Among the type B consumers who got a utility draw that is below the expected utility of the company searched first, all continue searching since any utility draw that is below the expected utility of the company searched first is always smaller than the reservation utilities of the potentially second-to-be-searched companies.

Thus the number of consumers who stop searching after the 1st search is $N_1 = \lambda N^{b1,A} + (1-\lambda)\,\gamma_1 N^{b1,A} + \lambda\delta_1 N^{b1,B}$. Let us define $w_1^A = \lambda + (1-\lambda)\,\gamma_1$ and $w_1^B = \lambda\delta_1$. Note that w_1^A and w_1^B denote the proportion of type A and type B consumers who stop searching after the 1st search among all type A and type B consumers, respectively. Then

$$N_1 = w_1^A N^{b1,A} + w_1^B N^{b1,B} \tag{18}$$

We can write the proportion of below-price expectation price draws among consumers who stop searching after the 1st search as a weighted average of the proportions of below-price expectation price draws among type A and among type B consumers weighted by the proportion of type A and type B consumers among those searching once. Suppose the proportion of type A consumers among all consumers who search once is $\rho_1 = \frac{N_1^{b1,A}}{N_1}$. Then the proportion of below-price expectation price draws among consumers searching once is

$$X_1 = \frac{\lambda}{w_1^A}\rho_1 + (1-\rho_1) \tag{19}$$

Intuitively speaking, $\lambda \leq \frac{\lambda}{w_1^A} \leq 1$ of type A consumers who stop after the first search have a below-price expectation price draw and all of type B consumers who stop after the 1st search have a below-price expectation price draw.

Suppose in the data we observe consumers making $k = 1, ..., K$ searches. Recall that the search method is identified if we can show for at least one consideration set size that we cannot get the same pattern under both simultaneous and sequential search. We showed that, under simultaneous search, the proportion of below-price expectation price draws in consumers' consideration sets is constant and equals λ for all k. Thus the search method is identified if we can show that

$$X_1 \neq \lambda \tag{20}$$

Note that $X_1 = \lambda$ *if and only if* $\rho_1 = 1$ and $w_1^A = 1$. Recall that ρ_1 denotes the proportion of type A consumers among all consumers searching once and w_1^A denotes the proportion of type A consumers who stop searching after the 1st search among all type A consumers. Then $X_1 = \lambda$ can only occur when there are only type A consumers among those who search once and in the data in general[8] (since $\rho_1 = 1$) and all consumers stop searching after the 1st search since all type A consumers got a price draw below their reservation price (since $w_1^A = 1$). Thus $X_1 = \lambda$ can only occur when we observe all consumers in the data to only search once. To summarize, under the sufficient but not necessary condition that we observe a positive number of consumers in the data to search more than once, under sequential search, the proportion of below-price expectation price draws in consumers' consideration sets of size one is always larger than λ and the search method is identified.

In Appendix B, we show analytically that this identifying pattern always holds for a variety of models describing homogeneous and differentiated goods. This includes models with unobserved heterogeneity in preferences and/ or search costs 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.

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 (2014) for more details. The identification of the

[8] If $N^B > 0$, then $w_1^B > 0$ and thus $\rho_1 < 1$.

parameters capturing differences in brand intercepts and other variables that vary across companies such as advertising spending 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).

Variables that do not vary aross companies, i.e. are consumer-specific, are identified by consumers with certain characteristics searching more or less than others. For example, suppose older consumers search less than younger consumers. Then - given that the search cost coefficient is identified by the average number of search across all consumers - older consumers must have a smaller benefit of searching, i.e. a lower utility for insurance, than younger consumers. Thus we would expect a negative coefficient for age 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 consumer-specific variables to shift search costs instead the utility.

5.3 Sequential Search Model

In the sequential search model, the parameters capturing differences in brand intercepts and variables that vary across companies such as advertising spending are identified from the conditions on the utilities and reservation utilities, i.e. equations (12), (13) and (15).

Search costs are identified from Weitzman's stopping rule (equation (6) or (13)). 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. 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 describes the relationship between utilities and reservation utilities.

Previous research (e.g. Kim et al. 2010) has shown that reservation utilities decrease when search costs increase. 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 (6) 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 (15)), 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.

In contrast to the simultaneous search model, variables in the utility function that do not vary across companies, i.e. are consumer-specific, are not identified in the sequential search model. The effects of these consumer-specific variables 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. The effects of these consumer-specific variables 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 variables 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 variables that do not vary by alternative in 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 describe how our analytical identification results discussed in the previous section allow us to determine the search method employed by consumers. We show that knowledge of the market-wide price distribution means, the companies in consumers' consideration sets and actual prices realized for the alternatives in the consideration sets identify the search method in both homogeneous and differentiated goods markets.

We have two objectives for the second set of simulation studies. 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). And second, we want to understand the consequences on estimates, model fit etc. of assuming an incorrect search strategy when estimating the model.

6.1 Generated Data

In all simulation studies, we generate data for 1,000 consumers (to mimic the size of the sample in our data). For homogeneous goods in the first set of simulation studies, we use the utility function $u_{ij} = -p_{ij}$ 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. For differentiated goods in the first and second set of simulation studies, we use a simple utility function with brand intercepts, price and advertising. We provide a detailed description of the model and generated data in Appendix C. We simulate data under the following two assumptions: (a) all consumers search simultaneously and (b) 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. 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. Lastly, 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.

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 homogeneous goods. As expected based on our discussion in the Identification section, under simultaneous search, the percentage of below-expected price actual prices in consumers' consideration sets is constant across all consideration set sizes. Since prices follow a normal distribution in our simulation studies, the proportion of below-expected price actual prices in consumers' consideration sets is about 50 percent. By contrast, under sequential search, the percentage of below-expected price actual prices in consumers' consideration sets of size one is 100 percent - much larger than 50 percent which would be expected under simultaneous search. Further, we see that the proportion of below-price expectation actual prices in consumers' consideration sets declines as consideration sets increase in size. As discussed in the Identification section, under sequential search, the declining pattern in the proportion of below-expected price actual prices in consumers' consideration sets is common.

The lower half of Table 1 shows the results for differentiated goods. Under simultaneous search, the percentage of below-expected price actual prices in consumers' consideration sets is again constant and around 50 percent across all consideration set sizes. Under sequential search, the percentage of below-expected price actual prices in consumers' consideration sets of size one is 87 percent and it declines to 50 and 40 percent for consideration sets of sizes two and three, respectively.

Figure 1 shows the distribution of consideration set sizes under both simultaneous and sequential search. Note that most consumers search three or fewer times under both search methods. Our identification strategy goes through as long as there is a positive number of consumers searching more than once. The data patterns in these simulation studies confirm and illustrate the results of the Identification section.

6.3 Data Patterns

Next, we briefly describe different data patterns (beyond those described in the previous section) that arise as a consequence of different search methods. We first discuss how consumers' search decisions change when their search method changes and then move on to discuss changes in purchase patterns as a consequence of changes in the search method. 64.50 percent of consumers search a different number of times across the two search methods. The average number of searches is 2.27 under simultaneous and 1.94 under sequential search. This represents a decrease of 14.5 percent in the average number of searches. Figure 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.[9] 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 percent of consumers search the same number of companies and 47.2 percent (17.3 percent) of consumers search fewer (more) companies under sequential versus simultaneous search. Now, we discuss how the search method influences consumers' purchase decisions. 15.70 percent of consumers change the company they purchase from solely as a consequence of the search method they use (since all the parameters and all generated data are held fixed). Among consumers who consider different sets of companies,[10] 24.3 percent purchase from different companies, while the remainder signs up with the same company under both search methods.

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

Table 2 displays the estimation results when the true DGP is known to the researcher. Column (i) shows the results when all consumers search simultaneously and column (ii) shows the results when all consumers search sequentially. Generally, our estimation approaches are able to recover consumer preferences and search costs well. 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 magnitude of the true values does not result in different sets of converged values.

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

[10] 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).

6.5 Unknown Search Method

As discussed in the Introduction section, most previous empirical research has made an assumption for the search method consumers use. In Table 3, we investigate the consequences of assuming the wrong search method on estimates and model fit. In column (i), the true search method consumers use is simultaneous, but the researcher assumes that it is sequential, while in column (ii) the true search method consumers use is sequential, but the researcher assumes that it is simultaneous. 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 (i) in Table 2 and column (i) in Table 3, the loglikelihood is worse on average across all 50 replications as well as *for every individual replication* when the wrong search method is assumed. A similar picture emerges by comparing the loglikelihoods from column (ii) in Table 2 and column (ii) in Table 3. These results indicate that imposing the wrong search method when estimating the model 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 an additional predictor of the correct search method.

The insights from our earlier discussion on the identification of the search method are crucial to understanding why the price and search cost coefficients are severely biased downwards and the model fit deteriorates under the incorrect search method assumption. In essence, when the data are generated under sequential search, the distribution of consideration set sizes has a longer right tail than it would have under simultaneous search as the true DGP. To accommodate this longer right tail when the model is estimated under simultaneous search, the net benefit of search Γ_{ik} (equation (3)) must be larger (for some consumers) to rationalize them having such larger consideration sets. In the estimation, a larger net benefit of search is achieved by a smaller price coefficient which increases the expected maximum utility among the searched companies (and thereby increases the net benefit of search) and by a smaller search cost coefficient which also increases the net benefit of search. This explains the downward bias of both the search cost and price coefficient when the true DGP is sequential search, but the model is estimated under the simultaneous search assumption.

Suppose the true DGP is simultaneous search, but a sequential search model is estimated. Under sequential search, a declining proportion of below-average prices is expected as consideration sets increase in size. Therefore, for larger consideration sets which were generated under simultaneous search, there are "too many" below-average prices in them than expected under sequential search, i.e.

the consumer must have continued searching even though he already had a low price option in his consideration set. This can be rationalized by the consumer either having very small search costs or being very insensitive to prices and explains the downward bias of the search cost and price coefficient when the true DGP is simultaneous search, but the model is estimated under the sequential search assumption.

Overall, our findings from the simulation studies are as follows: First, the pattern of prices in consideration sets identifies the search method consumers use. Next, our estimation approaches are able to recover consumer preferences and search costs well when the true DGP is known. When the wrong search method assumption is imposed in the estimation, true consumer preferences and search costs are no longer recovered. Further, when the model is estimated under both search method assumptions, the loglikelihood can be used as a reliable predictor of the true search method.

7 Empirical Application

We use data on consumer search and purchase behavior for auto insurance from an insurance shopping study conducted by a large marketing research company in 2006 and 2007. We observe which companies consumers collected price quotes from and which companies consumers signed up with. This gives us information on consumers' consideration sets 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 4 contains descriptive statistics of our data. We refer the reader to Honka (2014) for a detailed description of our data. As noted before, since consumers in our sample have been previously insured and coverage levels tend not to change much, assuming that consumers engage in price search and not in the search for other "attributes" is a reasonable assumption in this context.

We assume consumers have rational expectations about prices and 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.[11] We assume that prices follow a normal distribution with the mean being a function

[11] Note that Honka (2014) conducted extensive checks to ensure that using prices charged by previous insurers is a valid approach to estimating the market-wide distribution of insurance prices and does not suffer from a selection bias.

of the variables that determine insurance prices and a constant variance. The estimation results for the pricing regression are shown in Table 5. 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 (2014) for details on the price expectation estimation process.

7.1 Utilty Function

Consumer's utility for auto insurance is given by

$$u_{ij} = \alpha_j + \beta_1 p_{ij} + \beta_2 adv_{ij} + \beta_3 I_{ij,t-1} + Z_{ij}\gamma + \epsilon_{ij} \tag{21}$$

where adv_{ij} denotes consumer- and company specific recalled advertising. It is calculated as an interaction effect between consumer- and company-specific advertising recall and company-specific advertising spending. $I_{ij,t-1}$ 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. With an average retention rate of about 70 percent 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}: "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.[12] We chose to include these four factors as Honka (2014) has shown that they significantly influence consumers' utility 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 search 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 a consumer knows the price his previous insurer is going to charge him to renew his insurance

[12]Details on these demographic factors and summary statistics of the items that constitute them are available from the authors upon request.

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. $C_i = S_i \cup \left\{ j_{I_{ij,t-1}} \right\}$.

7.2 Model-free Evidence of Search Method

Table 6 displays the average proportion of below-expectation prices in consumers' consideration sets for the auto insurance data. Recall that insurance prices depend on consumer and policy characteristics. In estimating the distribution of prices we account for this by making the expected price a function of these consumer and policy characteristics. Thus when calculating the proportion of below-expectation prices we compare actual prices in consumers' consideration sets to consumer- and company-specific expected prices. Under simultaneous search, we expect the proportion to be constant across all consideration set sizes and to equal the probability of getting a below-expectation price draw, while under sequential search, we expect the proportion of below-expectation prices among consumers searching once to be larger than the probability of getting a below-expectation price draw. The average proportions of below-expectation prices in consumers' consideration sets clearly move around 50 percent and is constant across different consideration set sizes.[13] We interpret this as evidence for simultaneous search being the search method consumers use when shopping for auto insurance.

7.3 Estimation and Results

We need to adapt the estimation of both the simultaneous and the sequential search model compared to the ones shown in section 4 to reflect a specific setting of the auto insurance industry, namely, that consumers know the prices their previous insurance providers are going to charge them. For the simultaneous search model, we refer the reader to Honka (2014) for the estimation details. For the sequential search model, we refer the reader to Appendix D of this paper.

As described in the Model section, we need to make the assumption of first order stochastic dominance among the price distributions to use Chade and Smith (2005) and Honka (2014) to estimate the simultaneous search model. We do so by assuming that the variances of the company-specific price distributions are identical. We tested the appropriateness of this assumption in two ways: First, we conducted a Bartlett Test to test whether the company-specific variances of the price residuals from

[13] Note that few consumers in the data search six or more times. We are not able to calculate standard errors for consideration sets of size nine or ten since only one consumer makes that many searches in each case.

our pricing regression are equal. We were not able to reject the null hypothesis that all company-specific price residual variances are identical. Second, we estimated the EV Type I distribution of prices by making the scale parameter a function of company-fixed effects in addition to the location parameter being a function of consumer demographics, insurance policy characteristics and company-fixed effects. None of the firm fixed effects on the scale parameter was significant. We conclude that the assumption of identical price variances is appropriate in our context.

Column (i) in Table 7 shows the results under the assumption that all consumers search simultaneously, column (ii) shows the results under the assumption that all consumers search sequentially. The simultaneous search model fits the data better than the sequential search model. As discussed in section 6.5, the model fit is an additional predictor of the search method consumers use. Further, both the search cost and the price coefficient estimates under sequential search are very small. As outlined in section 6.5, when the true data generating process is simultaneous search but a sequential search model is estimated, we expect both the search cost and the price coefficient estimate to be severely biased downwards. Together with the model-free evidence from the previous section that also indicated that consumers search simultaneously, we find consistent evidence of simultaneous search being the search method consumers use when shopping for auto insurance. Given this overwhelming evidence we treat simultaneous search as the actual search method consumers use when shopping for auto insurance in the following sections. Our search cost estimate per search is \$42.09.[14] Note that the search cost estimate under simultaneous search is similar to the one (\$41.81) found by Honka (2014) using the same data and the same model (Model 0 in her paper). The small difference in search cost estimates can be explained by the different assumption on the price distributions noted previously.

7.4 Search Cost Elasticities

We predict the percentage change in companies' consideration and purchase market shares due to a 10 percent increase in search costs using simulation methods. Note that the search cost elasticity for purchase across all companies (in terms of purchased quantity) is zero in the auto insurance market 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 cost elasticities for purchase can be both positive and negative. Two effects determine search cost elasticities: First, some

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

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 search cost elasticity estimates need to be interpreted in light of this tradeoff for each company.

A 10 percent (100 percent) increase in search costs results in a 1.61 percent (42.27 percent) decrease in the average number of actively searched companies, i.e. excluding the free quote from the previous insurance provider. Table 8 shows percentage changes in consideration and purchase market shares due to a 10 percent increase in search costs. First, the consideration shares 21st Century, Mercury and MetLife decrease the most when search costs increase. Farmers, GMAC, Liberty Mutual, Safeco and Travelers increase their consideration shares. Second, 21st Century and Mercury lose most purchase market shares, while MetLife, Nationwide and Travelers win additional shares. And finally, consideration and purchase market shares do not necessarily move in the same direction (e.g. Metlife, Nationwide and Progressive).

8 How are companies affected by consumers' search method?

In this counterfactual, we explore 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 auto 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.

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.

Note that our model is a partial equilibrium model. Thus any counterfactuals only capture consequences on the demand side, i.e. we do not model premia adjustments on the supply side. The results can be interpreted as short-run market effects due to changes in the consumer search method.

8.1 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 the parameter estimates from column (i) in Table 7. In Section 7.3, we established that consumers use simultaneous search when shopping for auto insurance. Columns (i) and (iii) in Table 9 show the predicted consideration sets and purchases under this assumption for the search method. Columns (ii) and (iv) in Table 9 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 when changing the search method from simultaneous to sequential search comes from consumers stopping to search quickly if they get a low price draw early on in their search. Consideration set and purchase market shares under sequential search are very similar since consumers' consideration sets are small and all contain the previous insurance provider. 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 percent which is typical for this industry (see Honka 2014 and Israel 2005) and is also reflected by the large inertia coefficient in the estimation results.

If consumers 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 columns (iii) and (iv) in Table 9).[15] These customers decide to switch from their smaller previous insurers to the larger insurance companies as a result of the different search method. 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.

8.2 Effects on customer base

Now, we investigate 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 investigate "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.

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 find that the customers these five companies are gaining are mostly higher risk customers:[16] For example, the percentage of Geico customers with tickets in the past three years and an age of under 25 years increases by 25 percent and 56 percent, respectively. The percentage of State Farm customers with accidents in the past three years increases by 75 percent. Those two

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

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

results taken together show a mixed picture of a change in search method for the largest insurance companies: They gain market share, but these new customers are to a large extent higher 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.

9 Robustness Checks

9.1 Alternative Model Specifications

We check the robustness of our empirical results by estimating four alternative model specifications. As discussed in section 5.3, the effects of variables that do not change across companies such as demographics are not identified in the utility function under sequential search. We therefore estimate a simultaneous and sequential search model where those demographics enter through consumers' search costs instead of consumers' utility function. The results are shown in columns (i) and (ii) in Table 10. We find that for the simultaneous search model the estimates and the loglikelihood are very similar to column (i) in Table 7. For the sequential search model, we find that, as expected, the inclusion of the two demographics increases the loglikelihood. Additionally, both AIC and BIC support the inclusion of both variables. The other parameter estimates remain very similar to column (ii) in Table 7.

The sequential search model is also more flexible in that the assumption of first-order stochastic dominance among the price distributions is not necessary for estimation. Thus we estimate the sequential search model using company-specific price variances and the results are shown in column (iii) in Table 10. We find neither the parameter estimates nor the loglikelihood to change much compared to column (ii) in Table 7. This is likely due to the company-specific price variance being similar in the empirical data. Finally, in column (iv) of Table 10, we estimate a sequential search model with company-specific price variances 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 (iv) in Table 10) is still much smaller than the one of the less flexible simultaneous search model (column (i) in Table 7). We conclude our results are robust to alternative model specifications and that simultaneous search is the appropriate model assumption to describe consumer shopping behavior in the auto insurance industry.

9.2 Unobserved Heterogeneity

In the empirical application, heterogenity across consumers is captured via observable characterstics such as demographics as well as lagged choice (a la Guadagni and Little 1983). One concern could be the presence of unobserved heterogeneity in preferences, search costs and search method. Given the nature of our survey data, accounting for unobserved heterogeneity would typically not be possible. However, we have access to variables that could affect the search method such as credit scores that are unlikely to directly affect the utility of the alternatives. With information on these variables, we can appeal to a discrete-heterogeneity concomitant variables approach (see e.g., Dayton and Macready 1988) to distinguish those who search sequentially (consumers with high scredit scores) from those who search simultaneously (consumers with low credit scores). Now conditional on belonging to the 'segment' that searches sequentially (simultaneously), we can allow for the model parameters to be segment-specific. In effect we estimate a 2-segment, concomitant variables latent class model (Kamakura and Russell 1989) where one class of consumers searches simultaneously and the other class of consumers searches sequentially. While not reported here, we find that the size of the simultaneously searching consumer segment is .88 and the model estimates are very similar to the ones from Model (i) in Table 7. Search costs are estimated to be $42.11. We therefore conclude that our results are robust to this form of unobserved heterogeneity in the data.

10 Limitations and Future Research

There are several limitations to our research. First, 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. Second, 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 progress on answering important questions regarding the magnitudes of search costs and consequences of assumptions made in estimating models of search.

Third, our goal in this paper is to present search models that can be used in markets with any number of companies. To estimate the simultaneous search model in markets with a lot of alternatives, we have to assume that search costs are not company-specific. Note that this limitation has no implications for our search method identification strategy and that it can be overcome in markets with few alternatives by using a choice model approach a la Mehta et al. (2003). And finally, following the standard search literature our model assumes that consumers search to resolve uncertainty about a single product characteristic, i.e. 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 multiple product characteristics.

11 Conclusion

In this paper, we explore whether the search method consumers use can be deduced in data where consumer purchases and consideration sets, but not the sequence of searches, are observed. We show analytically that the search method is non-parametrically identified in those kind of data. Under simultaneous search, the average proportion of below-expectation price draws is constant across all consideration set sizes and equals the probability of getting a below-price expectation price draw, while under sequential search, the proportion of below-expectation price draws among consumers searching once is larger than the probability of getting a below-price expectation price draw.

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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Tables and Figures

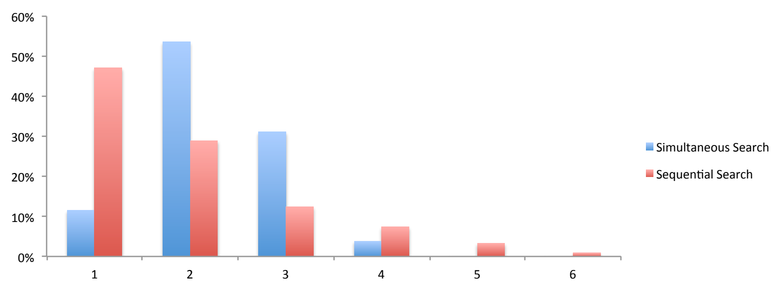

Figure 1: Number of Search

	Percentage of Below-Expected Price Actual Prices in Consideration Sets of Size					
	1	2	3	4	5	6
Homogeneous Goods						
Simultaneous Search		50.13	47.47			
Sequential Search	100.00	57.76	38.86	21.72	12.73	5.93
Differentiated Goods						
Simultaneous Search	50.40	50.90	49.80	51.30		
Sequential Search	86.60	49.90	39.80	30.40	27.90	25.90

Table 1: Monte Carlo Study Results on Search Method Identification

Assumption for ...		(i)		(ii)	
... Data Generation		Simultaneous Search		Sequential Search	
... Estimation		Simultaneous Search		Sequential Search	
	True Values	Means	Std. Error	Means	Std. Error
Brand 1	-2.0	-1.99	0.14	-1.96	0.14
Brand 2	-1.6	-1.72	0.14	-1.61	0.14
Brand 3	-2.1	-2.07	0.13	-2.05	0.13
Brand 4	-2.4	-2.27	0.13	-2.31	0.17
Brand 5	-1.4	-1.59	0.15	-1.44	0.18
Brand 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 2: Monte Carlo Studies Results with Known Search Method

Assumption for ...		(i)		(ii)	
... Data Generation		Simultaneous Search		Sequential Search	
... Estimation		Sequential Search		Simultaneous Search	
	True Values	Means	Std. Error	Means	Std. Error
Brand 1	-2.0	-2.34	1.58	-2.05	0.04
Brand 2	-1.6	-2.19	1.58	-1.85	0.07
Brand 3	-2.1	-2.33	1.58	-1.84	0.04
Brand 4	-2.4	-2.49	1.60	-2.18	0.04
Brand 5	-1.4	-1.73	1.59	-1.32	0.07
Brand 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 3: Monte Carlo Studies Results Under the Wrong Search Method Assumption

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Number of Quotes	945	2.96	1.38	1	10
Premium for 6-months Policy with Current Insurer	945	592.97	288.28	74	2,750
Number of Vehicles	945	1.58	0.64	1	3
Number of Drivers	945	1.64	0.59	1	4
Vehicle Year	945	2001.98	4.19	1960	2007
Respondent Age	945	45.23	12.94	20	84

Table 4: Descriptive Statistics
Prices are measured in dollars.

Variable	Estimate	Std. Error	Variable	Estimate	Std. Error
Constant	2.2886**	(.7624)	21st Century	.2374	(.5118)
Male	-.2063	(.1574)	AIG	.4593	(.4107)
Married	-.8474**	(.2718)	Allstate	-.1791	(.3049)
Divorced/ Separated	-.1308	(.2635)	American Family	-.6157	(.5088)
Widowed	.3808	(.7642)	Erie	-1.3207***	(.5062)
Domestic Partnership	-.1202	(.3344)	Farmers	-.3980	(.3936)
Age	-.0224***	(.0065)	Geico	-1.0452***	(.2972)
Driver under 25 Years	1.0810**	(.3316)	GMAC	.6378	(.6153)
Two Vehicles	2.0683***	(.1986)	The Hartford	-.7291	(.4461)
Three Vehicles	4.1097***	(.3031)	Liberty Mutual	.3033	(.3907)
Two Drivers	.3489	(.2683)	Mercury	.2958	(.5137)
Three Drivers	2.0738***	(.4954)	MetLife	.9811	(.5057)
Four Drivers	1.3158	(.9044)	Nationwide	-.4867	(.3926)
Medium City Suburb	.0366	(.2498)	Progressive	-.1205	(.3162)
Large City Suburb	.6730**	(.2491)	Safeco	.2390	(.5773)
Urban Area	1.0057***	(.2776)	Travelers	.7033	(.4416)
Home Owner Insurance			Chosen Coverage	yes	
with Current Insurer	-.1854	(.1720)	State	yes	
Other Insurance			Make*Class	yes	
with Current Insurer	-.2136	(.1746)			
Two or More Accidents	2.7329***	(.4659)			
Two or More Tickets	1.2601***	(.3656)			
Model Age	-.0566**	(.0182)	R^2	.72	

Table 5: Price Distribution
Prices are measured in $100.
**: <.001, **: <.01, *: < .05

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

Table 6: Average Proportion of Below-Expectation Prices in Insurance Data
Standard errors in parentheses.

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

Table 7: Results

Prices are measured in $100.

***: <.001, **: <.01, *: < .05

Company	Consideration	Purchase
21st Century	-3.75	-2.00
AIG	.17	.13
Allstate	-.22	-.48
American Family	-.69	-.03
Erie	-.20	-.07
Farmers	1.07	.00
Geico	.16	.45
GMAC	1.06	.00
The Hartford	.30	.11
Liberty Mutual	1.07	.24
Mercury	-2.00	-4.47
MetLife	-2.00	1.65
Nationwide	-.30	.92
Progressive	-.06	.01
Safeco	1.06	.00
State Farm	.31	.00
Travelers	1.07	.81

Table 8: Search Cost Elasticities due to a 10 Percent Increase in Search Costs

	(i)	(ii)	(iii)	(iv)
	Consideration Set Composition		Purchase Market Shares	
Company	Sim. Search	Seq. Search	Sim. Search	Seq. Search
21st Century	1.53	2.06	2.61	2.28
AIG	8.18	7.48	5.65	6.83
Allstate	14.24	12.03	11.96	10.52
American Family	4.18	3.61	4.24	3.80
Erie	2.91	3.49	2.93	2.71
Farmers	3.16	3.61	5.65	3.80
Geico	20.35	21.87	18.59	23.75
GMAC	.69	.31	.87	.33
The Hartford	4.80	3.86	5.33	3.36
Liberty Mutual	2.36	2.80	5.43	3.15
Mercury	1.20	1.62	1.74	1.84
MetLife	1.20	1.00	1.96	1.30
Nationwide	2.69	3.05	4.89	3.47
Progressive	16.32	18.19	15.00	18.76
Safeco	.36	.62	.65	.65
State Farm	14.57	13.08	10.33	11.82
Travelers	1.27	1.31	2.17	1.63

Table 9: Consideration Set and Purchase Market Share Predictions
Consideration Set and Purchase Market Shares are shown in Percent.

	(i)		(ii)		(iii)		(iv)	
Search Method	Simultaneous Search		Sequential Search		Sequential Search		Sequential Search	
Demographics	Search Costs		Search Costs				Search Costs	
Price Variances	Equal		Equal		Unequal		Unequal	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Brand Preferences								
21st Century	-1.7600***	(.1887)	.2929*	(.1328)	.2496	(.1413)	.2012	(.1355)
AIG	-1.2198***	(.1876)	.8188***	(.1221)	.8036***	(.1397)	.8200***	(.1308)
Allstate	-1.6359***	(.2087)	.7493***	(.1544)	.7350***	(.1627)	.7694***	(.1673)
American Family	-1.6130***	(.2388)	.8517***	(.1599)	.8461***	(.1491)	.7023***	(.1599)
Erie	-1.9251***	(.2173)	.6778***	(.1412)	.6510***	(.1499)	.7859***	(.1505)
Farmers	-1.8727***	(.2082)	.5166***	(.1284)	.4932***	(.1384)	.5987***	(.1486)
Geico	-2.2048***	(.2585)	.7799***	(.1593)	.7724***	(.1485)	.4424***	(.1531)
GMAC	-1.8382***	(.2938)	-.0035	(.1774)	-.0042	(.1663)	-.0505	(.1675)
Hartford	-1.7058***	(.1766)	.6840***	(.1531)	.6948***	(.1702)	.6484***	(.1699)
Liberty Mutual	-1.6335***	(.2169)	.4433**	(.1349)	.4244**	(.1475)	.3805*	(.1538)
Mercury	-1.8802***	(.2377)	.1985	(.1542)	.1746	(.1608)	.1470	(.1551)
MetLife	-1.6467***	(.2163)	.2304	(.2004)	.2100	(.2072)	.1644	(.2118)
Nationwide	-2.0378***	(.1845)	.3615*	(.1573)	.3399*	(.1616)	.2977	(.1859)
Progressive	-1.5266***	(.2132)	1.0271***	(.1357)	1.0060***	(.1268)	.9862***	(.1402)
Safeco	-2.1995***	(.2317)	-.1493*	(.0702)	-.0912	(.0617)	-.1547*	(.0719)
State Farm	-1.6474***	(.2059)	.8901***	(.1549)	.8713***	(.1438)	.3142*	(.1527)
Travelers	-1.6503***	(.1867)	.3266*	(.1631)	.3694*	(.1559)	.7492***	(.1494)
Other Parameters								
Price	-.4518***	(.0445)	-.0682***	(.0038)	-.0698***	(.0057)	-.0698***	(.0042)
Recalled Advertising	.1288**	(.0480)	.1281***	(.0182)	.1318***	(.0164)	.1244***	(.0162)
Inertia	.7194***	(.0783)	.6008***	(.0290)	.6001***	(.0244)	.5729***	(.0303)
Proven Reliability	.3430***	(.0541)	.0060	(.0229)	.0076	(.0199)	.0102	(.0254)
Out-of-Box Character	.1424**	(.0528)	.0759**	(.0240)	.0802*	(.0353)	.0762**	(.0279)
Search Costs								
Search Cost Constant	-1.6728***	(.2451)	-6.5425***	(.2811)	-6.2178***	(.3286)	-5.200***	(.3179)
Attitude Towards Auto Insurance Shopping & Switching	.3018	(.1655)	.4272***	(.1379)			.5359***	(.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 10: Robustness Check Results

Prices are measured in \$100.

***: <.001, **: <.01, *: < .05

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 is given by

$$P_{ij\Upsilon|\epsilon} = P(\min_{j\in S_i} u^*_{ij} \geq \max_{j'\notin S_i} u^*_{ij'} \quad \cap \quad \max_{j\in S_i} u_{ij} \geq u_{ij''}, \max_{j'\notin S_i} u^*_{ij'} \quad \cap \quad \bigcap_{l=2}^{k} \max_{t<l} \hat{u}_{it} < \hat{u}^*_{it=l} \quad \forall j'' \in S_i \backslash \{j\}, t = 2, \ldots, k)$$

This 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)

$$F(w_1, \ldots, w_M; s_1, \ldots, s_M) = \frac{1}{1 + \sum_{m=1}^{M} \exp(-s_m w_m)} \qquad \forall\, m = 1, \ldots, M \tag{A1}$$

where $s_1, \ldots, s_M$ are scaling parameters. McFadden (1989) suggests this kernel-smoothed frequency simulator which satisfies the summing-up condition, i.e. that probabilities sum up to one, 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^q_m
   (a) $\omega^q_{1|\epsilon} = \min\limits_{j\in S_i} u^*_{ij} - \max\limits_{j'\notin S_i} u^*_{ij'}$
   (b) $\omega^q_{2|\epsilon} = \max\limits_{j\in S_i} u_{ij} - u_{ij''}, \max\limits_{j'\notin S_i} u^*_{ij'}$
   (c) $\omega^q_{3\ldots M|\epsilon} = \bigcap_{l=2}^{T} \max\limits_{t<l} \hat{u}_{it} - \hat{u}^*_{it=l}$
3. Calculate smoothed search and purchase probabilities using equation (A1)
   $P^q_{ij\Upsilon|\epsilon} = \frac{1}{1+\sum_{m=1}^{M} \exp\left(-s_m w^q_{m|\epsilon}\right)}$
4. Integrate over the distribution of the ϵ_{ij} by averaging the search and purchase probabilities across all Q draws
   $P_{ij|\Upsilon} = \frac{1}{Q} \sum_{q=1}^{Q} P^q_{ij\Upsilon|\epsilon}$

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

Appendix B: Proof of Search Method Identification

In Section 5.1, we showed that under simultaneous search the proportion of below-price expectation price draws in consumers' consideration sets is constant and always equals λ (the probability of getting a below-price expectation price draw) for all consideration set sizes. The search method consumers use is identified if it is not possible to observe the same pattern under sequential search. The goal of this appendix is to first derive a general expression for the proportion of below-price expectation price draws in consumers' consideration sets without making any assumptions on the search cost and price distributions under sequential search and, second, to see whether it is possible that, under sequential search, the proportion of below-price expectation price draws equals λ - the same pattern as under simultaneous search.

Let r (with some abuse of notation) denote consumers' reservation price for homogeneous goods and consumers' reservation utility for differentiated goods. The proof of identification of the sequential search method depends on whether reservation prices/utilities are constant across consumers and companies, consumer-specific, company-specific or both. We will cover each case separately. Note that all of the commonly used demand specifications in search models fall into one of these four cases. More specifically, consumers' reservation prices/utilities are

1. constant across consumers and companies in models for
    - homogeneous goods with a market-wide price distribution and constant search costs
2. company-specific (but constant across consumers) in models for
    - homogeneous goods with company-specific price distributions and constant and company-specific search costs
    - homogeneous goods with a market-wide price distribution and company-specific search costs
3. consumer-specific (but constant across companies) in models for
    - homogenous goods with a market-wide price distribution and consumer-specific search costs
    - homogeneous goods with consumer-specific price distributions and constant or consumer-specific search costs
4. consumer- and company-specific in models for

- homogeneous goods with consumer- and company-specific search costs (no matter whether the price distribution is market-wide, consumer-, company-specific or both)
- homogeneous goods with consumer- and company-specific price distributions (no matter whether search costs are constant, consumer-, company-specific or both)
- homogeneous goods with company-specific price distributions and consumer-specific search costs
- homogeneous goods with consumer-specific price distributions and company-specific search costs
- differentiated goods with any price distribution and any search cost specification

We note two important things: First, while price distributions can be consumer- and/or company-specific, our proof relies on the assumption that the probability of getting a below-price expectation price draw is constant across consumers and companies, i.e. λ *cannot* have an i and/or j subscript. And second, we do not take a stand on whether these price distribution specifications can be an equilibrium outcome. We simply show that the search method is identified should they occur. We will first show proof of identification for case 3 and then for case 1 as it is a simplified version of case 3. Next, we establish proof for case 4 and then for case 3 as it is a simplified version of case 4.

Case 3: Consumer-Specific Reservation Prices r_i

Suppose there are $i = 1, ..., N$ consumers and $j = 1, ..., J$ companies in the market. 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-price expectation price draw being λ, i.e. $P(p < \mu) = \lambda$. Note that $0 < \lambda < 1$. Consumers have search costs c_i and make k_i searches. We assume that the distribution of search costs across consumers is well-defined distribution and unobserved by the researcher. Consumers have a reservation price r_i. Note that reservation prices r_i vary across consumers due to the (unobserved) heterogeneity in search costs.[17] The researcher does not observe reservation prices r_i. The search rule under sequential

[17] Note that the set-up for homogeneous goods with consumer-specific price distributions and constant or consumer-specific search costs is very similar: Prices follow some distribution $p \sim D_i(\mu_i, \sigma_i)$ with $P(p < \mu_i) = \lambda$. Search costs are constant or consumer-specific. This results is reservation prices that are consumer-specific. As long as μ_i and λ are observed (which we assume in all specifications), the proof proceeds as above and holds.

search defines that consumers stop searching *when and only when* they get a price draw below their reservation price r_i.

Suppose there are two types of consumers - type A and type B - with $N = N^A + N^B$. Type A consumers have a reservation price that is larger than the expected price, i.e. $r^A > \mu$, and type B consumers have a reservation price that is smaller than the expected price, i.e. $r^B \leq \mu$. Note that consumers do *not* change their type throughout the whole search process as their reservation prices r_i are constant across searches.

The ultimate goal of this exercise is to show whether and/or under what conditions the proportion of below-price expectation price draws among consumers searching k times can equal λ. In order to show this, we need to calculate the proportion of below-price expectation price draws among consumers searching once X_1, the proportion of below-price expectation price draws among consumers searching twice X_2, etc.

Consumers Searching Once

Before the 1st search, there are N consumers ready to search.[18] Since prices are randomly and independently drawn, $\lambda\left(N^A + N^B\right)$ consumers draw a below-price expectation price.

- All type A consumers who got a below-price expectation price draw, stop searching after the 1st search since any below-price expectation price draw is always smaller than their reservation prices which are larger than the expected price.

- Among the type B consumers who got a below-price expectation price draw, a proportion $0 \leq \delta_1 \leq 1$ stops searching since their price draws were below their reservation prices which are smaller than the expected price and a proportion $(1 - \delta_1)$ continues to search since their price draws were above their reservation prices which are smaller than the expected price.

$(1 - \lambda)\left(N^A + N^B\right)$ consumers draw an above-price expectation price:

- Among the type A consumers who got an above-price expectation price draw, a proportion $0 \leq \gamma_1 \leq 1$ stops searching since their price draws were below their reservation prices which are larger than the expected price and a proportion $(1 - \gamma_1)$ continues to search since their price draws were above their reservation prices which are larger than the expected price.

[18] Without loss of generality we assume that all consumers searches at least once.

- Among the type B consumers who got an above-price expectation price draw, all continue searching since any above-price expectation price draw is always larger than their reservation prices which are below the expected price.

Thus the number of people who stop searching after the 1st search is $N_1 = \lambda N^A + (1-\lambda)\gamma_1 N^A + \lambda\delta_1 N^B$. Let us define $w_1^A = \lambda + (1-\lambda)\gamma_1$ and $w_1^B = \lambda\delta_1$. Note that w_1^A and w_1^B denote the proportion of type A and type B consumers who stop searching after the 1st search among all type A and type B consumers, respectively. Then

$$N_1 = w_1^A N^A + w_1^B N^B \tag{B1}$$

with $0 \leq w_1^B \leq \lambda \leq w_1^A \leq 1$ following from the assumptions for $\lambda, \delta_1, \gamma_1$. The number of people who continue to search after the 1st search is

$$N^c = \left(1 - w_1^A\right) N^A + \left(1 - w_1^B\right) N^B \tag{B2}$$

$(1-\lambda)(1-\gamma_1) N^A + (1-\lambda) N^B$ consumers continue searching after an above-price expectation price draw and $\lambda(1-\delta_1) N^B$ consumers continue searching after a below-price expectation price draw.

We can write the proportion of below-price expectation price draws among consumers who stop searching after the 1st search as a weighted average of the proportions of below-price expectation price draws among type A and among type B consumers weighted by the proportion of type A and type B consumers among those searching once. Suppose the proportion of type A consumers among all consumers who search once is $\rho_1 = \frac{N_1^A}{N_1}$. Then the proportion of below-price expectation price draws among consumers searching once is

$$X_1 = \frac{\lambda}{w_1^A}\rho_1 + (1-\rho_1) \tag{B3}$$

Intuitively speaking, $\lambda \leq \frac{\lambda}{w_1^A} \leq 1$ of type A consumers who stop after the first search have a below-price expectation price draw and all of type B consumers who stop after the 1st search have a below-price expectation price draw.

Is the Search Method Identified?

Suppose in the data we observe consumers making $k = 1, ..., K$ searches. Recall that the search method is identified if we can show for at least one consideration set size that we cannot get the same pattern under both simultaneous and sequential search. We showed that, under simultaneous search, the proportion of below-price expectation price draws in consumers' consideration sets is constant and equals λ for all k. Thus the search method is identified if we can show that

$$X_1 \neq \lambda \tag{B4}$$

Note that $X_1 = \lambda$ *if and only if* $\rho_1 = 1$ and $w_1^A = 1$. Recall that ρ_1 denotes the proportion of type A consumers among all consumers searching once and w_1^A denotes the proportion of type A consumers who stop searching after the 1st search among all type A consumers. Then $X_1 = \lambda$ can only occur when there are only type A consumers among those who search once and in the data in general[19] (since $\rho_1 = 1$) and all consumers stop searching after the 1st search since all type A consumers got a price draw below their reservation price (since $w_1^A = 1$). Thus $X_1 = \lambda$ can only occur when we observe all consumers in the data to only search once. To summarize, under the sufficient but not necessary condition that we observe a positive number of consumers in the data to search more than once, under sequential search, the proportion of below-price expectation price draws in consumers' consideration sets of size one is always larger than λ and the search method is identified.

Case 1: Constant Reservation Prices r

Suppose all consumers have the same search cost c. Then all consumers also have the same reservation price r. Since prices are randomly and independently drawn across consumers and searches, the proportion of consumers who get a below-reservation price price draw is constant across searches, i.e. $\gamma_1 = \gamma_2$ and $\delta_1 = \delta_2$ and following from that $w_1^A = w_2^A = w^A$ and $w_1^B = w_2^B = w^B$. All consumers belong to one type since all consumers have the same reservation price.

Suppose there are only type B consumers in the market, i.e. $N = N^B$ and $\rho_1 = \rho_2 = 0$. Then the proportion of below-price expectation price draws in consumers' consideration sets of size one is

[19] If $N^B > 0$, then $w_1^B > 0$ and thus $\rho_1 < 1$.

$$X_1 = 1 \geq \lambda \tag{B5}$$

Suppose there are only type A consumers in the market, i.e. $N = N^A$ and $\rho_1 = \rho_2 = 1$. Then

$$X_1 = \frac{\lambda}{w_A} \geq \lambda \tag{B6}$$

since $0 \leq w_1^A \leq 1$. Thus under the same sufficient, but not necessary condition that there is a positive number of consumers who search more than once, under sequential search the proportion of below-price expectation price draws in consideration sets of size one is always larger than λ and the sequential search method is identified.

Case 4: Consumer- and Company-Specific Reservation Prices r_{ij}

Since differentiated goods are of particular interest to researchers, we will show search method identification for them. An analogue proof can be derived for the various homogeneous goods specifications discussed under case 4 at the beginning of Appendix B.

The following set-up is taken from Weitzman (1979): Suppose there are $i = 1, ..., N$ consumers and $j = 1, ..., J$ companies in the market. Consumers have a utility function such as $u_{ij} = \alpha_j + \beta p_{ij} + X_{ij}\gamma + \epsilon_{ij}$ with $\beta < 0$ 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 $p \sim D_j\left(\mu_j^p, \sigma_j^p\right)$ with the probability of getting a below-mean price price draw being λ, i.e. $P\left(p < \mu_j^p\right) = \lambda$. Note that $0 < \lambda < 1$. Consumers have search costs c_{ij} and make k_i searches. Consumers have reservation prices r_{ij}. Note that for differentiated goods reservation utilities r_{ij} vary across consumers and companies due to consumers' utilities varying across consumers and companies (and also potentially due to consumer- and company-specific search costs as in this example).

Given the assumptions for the price distributions, consumers' utility function also follows distribution D_j, i.e. $u_{ij} \sim D_j\left(\mu_{ij}, \sigma_j\right)$ with $\mu_{ij} = \alpha_j + \beta\mu_j^p + X_{ij}\gamma + \epsilon_{ij}$ and $\sigma_j = \gamma\sigma_j^p$. Further, since $P\left(p < \mu_j^p\right) = \lambda$, it must be that $P\left(u > \mu_{ij}\right) = \lambda$, i.e. a below-price expectation price draw always results in an above-mean utility utility.

Using Weitzman's (1979) selection rule, we know that consumers order all alternatives in a decreasing order of their reservation utilities r_{ij}. Consumers first search the alternative with the highest, then the alternative with the second highest etc. reservation utility. To express the ranking according to the reservation utilities r_{ij}, let us define $r_{i,t=1}$ as the company with the highest reservation utility for consumer i, $r_{i,t=2}$ as the company with the second-highest reservation utility for consumer i etc. Using Weitzman's (1979) stopping rule, we know that consumers stop searching when the maximum utility among the searched alternatives is larger than the maximum reservation utility among the non-searched companies.

Before the 1st search we can differentiate between two types of consumers - type A and type B - with $N = N^{b1,A} + N^{b1,B}$. For type A consumers, the reservation utility of the potentially second-to-be-searched company is smaller than the expected utility of the company searched first, i.e. $r_{i,t=2} < \mu_{i,t=1}$, and for type B consumers, the reservation utility of the potentially second-to-be-searched company is larger than the expected utility of the company searched first, i.e. $r_{i,t=2} \geq \mu_{i,t=1}$. Note an important difference compared to the consumer type definitions used in the proof of cases 1 and 3: In cases 1 and 3, consumers remained the same type throughout their whole search process. Here, as well as later in case 2, consumers can change their type, i.e. change from being type B to being type A consumers (but not vice versa!). Therefore $b1$ in $N^{b1,A}$ and $N^{b1,B}$ stands for the number of consumers belonging to type A and type B, respectively, before the 1st search - hence $b1$.

Consumers Searching Once

Before the 1st search there are N consumers ready to search.[20] Since prices are randomly and independently drawn, $\lambda \left(N^{b1,A} + N^{b1,B} \right)$ consumers get a utility draw that is above the expected utility of the company searched first (due to a below-price expectation price draw):

- All type A consumers who got a utility draw that is above the expected utility of the company searched first, stop searching after the 1st search since any utility draw that is above the expected utility of the company searched first is always larger than the reservation utility of the potentially second-to-be-searched company $r_{i,t=2}$.
- Among the type B consumers who got a utility draw that is above the expected utility of the company searched first, a proportion $0 \leq \delta_1 \leq 1$ stops searching since their utility draws were larger than the reservation utilities of the potentially second-to-be-searched companies $r_{i,t=2}$

[20] Without loss of generality we assume that all consumers search at least once.

and a proportion $(1-\delta_1)$ continues to search since their utility draws were below the reservation prices of the potentially second-to-be-searched companies.

$(1-\lambda)\left(N^{b1,A}+N^{b1,B}\right)$ consumers get a utility draw that is below the expected utility of the company searched first (due to an above-price expectation price draw):

- Among the type A consumers who got a utility draw that is below the expected utility of the company searched first, a proportion $0 \leq \gamma_1 \leq 1$ stops searching since the utility draws were larger than the reservation utilities of the potentially second-to-be-searched company $r_{i,t=2}$ and a proportion $(1-\gamma_1)$ continues to search since their utility draws were below the reservation utilities of the potentially second-to-be-searched company.

- Among the type B consumers who got a utility draw that is below the expected utility of the company searched first, all continue searching since any utility draw that is below the expected utility of the company searched first is always smaller than the reservation utilities of the potentially second-to-be-searched companies.

Thus the number of consumers who stop searching after the 1st search is $N_1 = \lambda N^{b1,A} + (1-\lambda)\gamma_1 N^{b1,A} + \lambda\delta_1 N^{b1,B}$. Let us define $w_1^A = \lambda + (1-\lambda)\gamma_1$ and $w_1^B = \lambda\delta_1$. Note that w_1^A and w_1^B denote the proportion of type A and type B consumers who stop searching after the 1st search among all type A and type B consumers, respectively. Then

$$N_1 = w_1^A N^{b1,A} + w_1^B N^{b1,B} \tag{B7}$$

with $0 \leq w_1^B \leq \lambda \leq w_1^A \leq 1$ following from the assumptions for $\lambda, \delta_1, \gamma_1$. The number of people who continue to search after the 1st search is

$$N^c = \left(1-w_1^A\right) N^{b1,A} + \left(1-w_1^B\right) N^{b1,B} \tag{B8}$$

$(1-\lambda)(1-\gamma_1) N^{b1,A} + (1-\lambda) N^{b1,B}$ consumers continue searching after a below-expected utility utility draw and $\lambda(1-\delta_1) N^{b1,B}$ consumers continue searching after an above-expected utility utility draw.

We can write the proportion of below-price expectation price draws among consumers who stop searching after the 1st search as a weighted average of the proportions of below-price expectation price draws among type A and among type B consumers weighted by the proportion of type A and type B consumers among those searching once. Suppose the proportion of type A consumers among all consumers who search once is $\rho_1 = \frac{N_1^{b1,A}}{N_1}$. Then the proportion of below-price expectation price draws among consumers searching once is

$$X_1 = \frac{\lambda}{w_1^A}\rho_1 + (1 - \rho_1) \tag{B9}$$

Intuitively speaking, $\lambda \leq \frac{\lambda}{w_1^A} \leq 1$ of type A consumers who stop after the first search have a below-price expectation price draw and all of type B consumers who stop after the 1st search have a below-price expectation price draw.

Is the Search Method Identified?

Note that equation (B9) is identical to equation (B3). Thus the search method is identified under the same sufficient but not necessary condition that there is a positive number of consumers who search more than once. Under simultaneous search, the proportion of below-price expectation price draws among consumers searching once equals the probability of getting a below-price expectation price draw λ. Under sequential search, the proportion of below-price expectation price draws among consumers searching once is larger than the probability of getting a below-price expectation price draw λ.

Case 2: Company-Specific Reservation Prices r_j

Suppose prices follow a market-wide distribution $p \sim D(\mu, \sigma)$ and search costs are company-specific c_j. This results in consumers having company-specific reservation prices r_j.[21] Consumers rank companies in an increasing order of the reservation prices r_j (Weitzman 1979). Since reservation prices are not consumer-specific, all consumers search the same company (with the lowest reservation price) first and all consumers (before the 1st search) belong to either type A and type B. Suppose all consumers belong to type B before the 1st search. Then we get the same result as in equation (B5). Suppose all consumers belong to type A before the 1st search. Then we get the same result as in equation (B6). Thus under the same sufficient but not necessary condition that there is a positive number of consumers

[21] Note that the set-up for homogeneous goods with company-specific price distributions and constant or company-specific search costs is very similar: Prices follows some distribution $p \sim D_j(\mu_j, \sigma_j)$ with $P(p < \mu_j) = \lambda$. Search costs are constant or company-specific. This results is reservation prices that are company-specific. As long as μ_j and λ are observed by the researcher (which we assume in all specifications), the proof proceeds as above and holds.

who search more than once, under sequential search the proportion of below-price expectation price draws in consideration sets of size one is always larger than λ and the search method is identified.

Addendum: Proportion of Below-Price Expectation Price Draws Across k Searches Under Sequential Search

We can generally write the proportion of below-price expectation price draws among consumers searching k times as

$$X_k = \frac{1}{k}\left(\sum_{l=1}^{k-1} \frac{\lambda - w_l^B}{1 - w_l^B}\left(1-\rho_k\right) + \frac{\lambda}{w_k^A}\rho_k + \left(1-\rho_k\right)\right) \tag{B10}$$

with $0 \leq w_k^B \leq \lambda \leq w_k^A \leq 1$ and $0 \leq \rho_k \leq 1$ for all k.[22] Depending on the model, we can place further restrictions on the parameters w_k^A and w_k^B:

- For models falling under case 1, it must be that $w_k^A = w_{k+1}^A$ and $w_k^B = w_{k+1}^B$ for all k.
- For models falling under case 3, it must be that $w_k^A \geq w_{k+1}^A \geq \lambda$ and $\lambda \geq w_k^B \geq w_{k+1}^B$ for all k.
- For models falling under cases 2 and 4, we cannot place further restrictions on w_k^A and w_k^B.

Further note that for models falling under cases 1 and 3 we observe the minimum and maximum for $\rho_1, ..., \rho_K$ in the data:

- Consumers whom we observe to only have above-price expectation price draws in their consideration sets must be type A since type B consumers would have continued searching until they would have found at least one below-price expectation price draw. Since we observe the number of consumers searching k times N_k and the number of consumers with only above-price expectation price draws in their consideration sets of size k, we can calculate $\min(\rho_k)$.
- Consumers whom we observe to have at least two below-price expectation price draws in their consideration sets must be type B consumers since type A consumers would have stopped searching after the first below-price expectation price draw. We need at least two below-price expectation price draws since we do not observe the search sequence and have to rule out the case that a consumer is type A and just got by chance a below-price expectation price draw in his

[22]The derivation of equation (B10) is available from the authors upon request.

last search. This gives the minimum number of type B consumers searching k times among all consumers searching k for consideration sets of size 2 or larger and allows us to calculate $\min(1-\rho_k)$ which is equivalent to $\max(\rho_k)$ for all $k \geq 2$.

Appendix C: Data for Monte Carlo Simulations

Generated Data

In all simulation studies, we generate data for 1,000 consumers. For homogeneous goods, we use the utility function $u_{ij} = -p_{ij}$ 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. For differentiated goods, 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 5 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.

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 (2014) for auto insurance. The advertising coefficient was set to .5 in the simulations.

Data Description

The search method has a large effect on company's customer bases. We find that between 25 to 59 percent of a company's customer base changes when consumers change their search method from simultaneous to sequential. This change is coming from customers either no longer buying from a company or newly buying from a company.[23] From a company's perspective, a change in search method has dramatic consequences on its customer base. We also find that the larger a company's market share, the smaller the effect of a change in search method on its customer base is.

Now, we describe 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

[23] 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).

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 ranging from 6 to 25 percent.

	(i) Simultaneous Search	(ii) Searches Search	(iii) 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 C-1: Consideration Percentages in Percent

	(i)	(ii)	(iii)	(iv)	(v)
	Purchase Market Shares		Conversion 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 C-2: Purchase Market Shares and Conversion Rates and Their Change in Percent

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 to a specific setting in the auto insurance industry: Insurance companies send their customers "free" renewal offers. "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 (12) from the paper can remain as it is. We then need to adapt equations (13) - (16): 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.

$$\max_{j \in C_i} u_{ij} \geq u_{ij'}, \max_{j'' \notin S_i} r_{ij''} \qquad \forall j' \in C_i \setminus \{j\} \tag{D1}$$

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 (equation (15) in the paper) must be adapted to

$$\bigcap_{l=2}^{k+1} \max_{t<l-1} \left(\hat{u}_{ij_{PI}}, \hat{r}_{it}\right) < \hat{r}_{it=l-1} \tag{D2}$$

The probability of observing a consumer search a set of companies Υ and purchase from company j under sequential search is then given by

$$P_{ij\Upsilon} = P(\min_{j \in S_i} r_{ij} \geq \max_{j' \notin S_i} r_{ij'} \cap \max_{j \in C_i} u_{ij} \geq u_{ij'}, \max_{j'' \notin S_i} r_{ij''} \bigcap_{l=2}^{k+1} \max_{t<l-1} \left(\hat{u}_{ij_{PI}}, \hat{r}_{it}\right) < \hat{r}_{it=l-1} \quad \forall j' \in C_i \backslash \{j\}, t = 2, \ldots, k) \tag{D3}$$

and the loglikelihood of the model is shown in equation (17).

Appendix E: Wrong Assumptions

1. Unequal Variances in Price Distributions

In the paper, 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 make 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 able to recover the true values. And second, we investigate the consequences of the equal variance assumption on the estimates when the data are generated with company-specific price variances under both search methods.

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 of the paper 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. Further, to generate the data under simultaneous search, we can no longer rely on the ranking according to the expected indirected utilities. Instead, we simulate 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 (i) in Table E-1 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 (ii) and (iii) 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 (ii)), 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 (iii)), 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) or \$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, to have some reassurance regarding the results.

2. Identical Search Costs Across Companies

In the paper, we assume that search costs are identical across companies. This assumption is necessary for the simultaneous search model and it allows us to apply the theory developed by Chade and Smith (2005). This assumption is not necessary for the sequential search model, but we nevertheless make it to keep everything constant across the two search methods. Here 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 able to recover the true values. And second, we investigate 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 in the paper 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. Furthermore, to generate the data under simultaneous search, we can no longer rely on the ranking according to the expected indirected utilities. Instead, we simulate 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 (i) in Table E-2 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 (ii) and (iii) 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 (ii)), 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 (iii)), 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. 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 set of simulation studies 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. Our results indicate that it is important that the assumption of identical search costs holds in the data, especially for the simultaneous search model, to have some reassurance regarding our results.

Assumptions for ...		(i)		(ii)		(iii)	
... Data Generation							
Price Variances		Unequal		Unequal		Unequal	
Search Method		Sequential		Simultaneous		Sequential	
... Estimation							
Price Variances		Unequal		Equal		Equal	
Search Method		Sequential		Simultaneous		Sequential	
	True Values	Means	Std. Error	Means	Std. Error	Means	Std. Error
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 E-1: Monte Carlo Studies Results with Regard to Different Assumptions for Price Variances

Assumptions for ...		(i)		(ii)		(iii)	
... Data Generation							
Search Costs		Company-Specific		Company-Specific		Company-Specific	
Search Method		Sequential Search		Simultaneous Search		Sequential Search	
... Estimation							
Search Costs		Company-Specific		Identical		Identical	
Search Method		Sequential Search		Simultaneous Search		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	
BIC		6,128.61		6,752.29		6,386.24	

Table E-2: Monte Carlo Studies Results with Regard to Different Assumption for Search Costs