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Quantifying search and switching costs in the US auto insurance industry

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I estimate demand for auto insurance in the presence of two types of market frictions: search and switching costs. I develop an integrated utility-maximizing model in which consumers decide over which and how many companies to search and from which company to purchase. My modelling approach rationalizes observed consideration sets as being the outcomes of consumers' search processes. I find search costs to range from $35 to $170 and average switching costs of $40. Search costs are the most important driver of customer retention and their elimination is the main lever to increase consumer welfare in the auto insurance industry.

1. Introduction

■ Insurance markets can be inefficient for several reasons. Starting with Akerlof (1970) adverse selection is the potential source of market inefficiency that has received most attention by academics (see Einav, Finkelstein, and Levin, 2010 for a literature review). In this article, I focus on a different potential reason, market frictions, and estimate demand for insurance in their presence. I study two types of market frictions, namely, consumer search and switching costs. I define search costs as the cost to the consumer of conducting one search and switching costs as the cost a consumer incurs upon switching insurance providers after the search has been completed. If one or both are found to be substantial in magnitude, this would suggest that they need to be accounted for when estimating demand for insurance. Further, it could significantly change the results of subsequent analyses such as welfare calculations.

Quantifying market frictions is important for reasons beyond analyzing how efficient the market is. First, accounting for consumers' limited information is necessary to recover true consumer preferences. Previous research (e.g., Sovinsky, 2008; Ching, Erdem, and Keane, 2009; Draganska and Klapper, 2011; De los Santos, Hortaçsu, and Wildenbeest, 2012; Koulayev, 2014;

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Pires, 2013; Seiler, 2013) has shown that consumer preference estimates are biased when consumers have limited information and this aspect is ignored in the demand estimation. For example, De los Santos, Hortaçsu, and Wildenbeest (2012) find own-price elasticities under the assumption of costly search (limited information) to be three to six times larger (in absolute terms) than under full information. Second, both search and switching costs can increase companies' market power and lead to higher prices for consumers.[1] To determine the importance of these market rigidities, it is necessary to quantify them. Finally, search and switching costs can play an important role in managers' pricing and advertising decisions. For example, if switching costs are large, an "invest-and-harvest" pricing strategy might be optimal for insurance companies.

A novel feature of my article is that I use data that contain information not only on consumers' purchases, but also on individual-specific consideration sets. The need to estimate market frictions with data where both search and purchase decisions are observed has been pointed out by survey articles in several streams of literature related to this article. Farrell and Klemperer (2007) emphasize the importance of individual-level choice data in identifying switching costs. Ratchford (2008) stresses the need for data in which consumers' consideration sets are observed for a clean identification of search costs. Finally, Einav, Finkelstein, and Levin (2010) underscore the need for such data especially in the context of insurance markets, where contract terms and prices are highly customized. By using individual-level data on consideration sets and purchases from the US auto insurance industry, I am able to address these demands and to cleanly identify search and switching costs with fewer assumptions than used by previous literature.

The US auto insurance industry exhibits many characteristics that indicate that search and switching costs play an important role in consumers' decisions. First, the industry is characterized by a very high retention rate. According to industry sources, around 70% of customers stay with their insurance provider after a one-year contract period, and this percentage increases with customer tenure.[2] Further, industry sources state that consumers only collect 2.4 quotes on average before making a purchase decision. At the same time, insurance companies advertise potential annual savings of around $400 when switching insurance providers. For example, the insurance company The Hartford claims on its website (November 13, 2009) annual savings of approximately $402 upon switching. Another insurer, Esurance, introduced a "Switch & Save Discount" where new customers can save an additional 5% on their first year premia. One explanation for such a high retention rate and for the level of advertised savings is the presence of consumer search and switching costs.

High retention rates, such as those observed in the US auto insurance industry, can be problematic if they are not driven by customer satisfaction but by market rigidities such as search and switching costs. Israel (2005b) finds that consumers who stay with their insurance provider after a not-at-fault accident do so because they have either learned about the good quality of their insurance provider or because switching costs are so high that they prevent consumers from switching. Because of the nature of his data, Israel (2005b) is unable to differentiate between these two explanations. In contrast, in this article, I disentangle the part of customer inertia that stems from customer satisfaction from the part that comes from consumer switching costs because I observe customers' satisfaction levels and their switching behavior. Further, the question of how consumers make their purchase decisions has not been studied because almost all data used by previous research on auto insurance are comprised of auto insurance purchase histories from a *single* insurance company. Because of the unique characteristics of my data, in that I observe which companies consumers considered and which premia they were quoted, I am able to fill this gap in the literature.

A few articles have estimated either search or switching costs for auto insurance plans. Dahlby and West (1986) estimate search costs for auto insurance for consumers in Alberta

[1] Some researchers have found switching costs to make certain markets more competitive (Dubé, Hitsch, and Rossi, 2009).

[2] This pattern is also described by Israel (2005a).

(Canada) in the seventies. Berger, Kleindorfer, and Kunreuther (1989) estimate a model where auto insurance customers incur switching costs (only). Cummins, McGill, Winklevoss, and Zelten (1983) estimate switching costs to equal 20% of the premium paid. These articles suffer from several shortcomings. First, they focus on only one type of market friction (either search or switching costs) and ignore the other one. This can be problematic, as Wilson (2012) has shown analytically, because in markets where both types of cost are present, cost estimates based on models with only one type of cost are biased upward. Second, in each of these articles the identification of either type of market friction comes from functional form and not directly from variation in the data. This is because the authors neither observe consumer search nor switching behavior. This is especially evident in the case of Dahlby and West (1986) and Berger, Kleindorfer, and Kunreuther (1989) who use the same data to estimate models where either only search or only switching costs are included. A recent article related to mine is Handel (2013). He estimates inertia between different health insurance plans for one employer. In contrast, I estimate inertia between different auto insurance companies (for the same insurance plans) and, in addition, quantify the costs of collecting price information for and switching insurance plans.

I study a consumer's auto insurance policy purchase decision after he has decided on the various policy characteristics he would like (i.e., coverage levels, etc.). Thus, I assume that consumers want to buy the same (or very similar) insurance policy from each available insurance company. To quantify the search and switching costs consumers incur while shopping for auto insurance, I develop an integrated utility-maximizing model that describes consumers' consideration and purchase decisions, that is, how many and which companies to consider and with which company to sign. Before engaging in search, I assume that consumers know all firms' characteristics except premia. I assume consumers have expectations about prices which are based on the premia they and other consumers have paid in the past. Further, I assume that consumers know the premium their previous insurer will charge them to renew their insurance policy. Consumers must engage in search to learn about actual prices charged by all companies except their previous insurer. Because search is costly, consumers search only a limited number of firms which, together with the quote from their previous insurer, make up their consideration sets. Explicitly characterizing consideration sets requires an assumption on the type of search method (simultaneous versus sequential) that the consumer follows. Here, I assume a simultaneous search approach. Once consumers have decided which and how many companies to consider, they collect quotes from all companies in their consideration sets and all uncertainty regarding prices is resolved. Finally, consumers choose an insurer from their consideration set. I jointly estimate both parts (consideration and choice) of my model.

My results indicate substantial search and switching costs for the US auto insurance industry. Average switching costs are about \$40; the cost of one price search over the Internet is about \$35, whereas the cost of a price search through local agents, mail, and calling centers ranges from \$100 to \$170.[3] I find consumer search costs to be the main driver of the high retention rate found in the auto insurance industry when compared with switching costs and customer satisfaction. Further, the results regarding consumer welfare indicate that the increase in consumer welfare stemming from an elimination of search costs is 17 times larger than the welfare increase stemming from an elimination of switching costs. Finally, I provide evidence that the majority of the consumer welfare increase after a removal of search costs is coming from consumers' "option value" of being able to choose from more companies and that the predicted premium savings are moderate.

The remainder of this article is organized as follows: in the next two sections, I describe some institutional details of the US auto insurance industry and present the data. In Section 4, I introduce the model followed by a discussion of the estimation approach and model identification in Sections 5 and 6. In the next two sections, I present the results and two counterfactuals. I make suggestions for future research in Section 9 and conclude in the last section.

[3] Although I estimate channel-specific search costs, I do not model consumers' decisions which quoting channel(s) to use to collect price quotes.

2. The US auto insurance industry

■ The net premia written in the property and casualty insurance in the United States equaled \$447.9 billion (after reinsurance transactions, excluding state funds) in 2007, according to the National Association of Insurance Commissioners (NAIC). About 500,000 people were employed by direct property and casualty insurers in 2008 according to the US Bureau of Labor Statistics. The largest line of business in the property and casualty insurance sector, accounting for more than one third of the net premia written (\$159.7 billion in 2007), is private passenger auto insurance. The national average expenditure for auto insurance in 2006 was \$817, down 1.7% from 2005.

Several features of the US private passenger auto insurance industry are worth mentioning. First, it is a very fragmented industry. In 2007, the five largest (in market share) auto insurance groups together had a market share of less than 50%. During the last decade, the "old" market leaders—State Farm and Allstate—have lost market share, whereas "new," Internet-focused insurance groups—Progressive and Berkshire Hathaway (i.e., Geico)—have roughly doubled their market shares. Second, it is a highly regulated industry. All states, except for Wisconsin, require auto insurance companies to file all form and rate changes with each state's insurance commissioner, that is, all price changes fall under the Freedom of Information Act (FOIA) and are publicly known. Third, all premia values have to be argued on the basis of cost and are subject to approval by state insurance commissioners. Fourth, any premia and premium changes have to be based on allowed observable customer characteristics. Both which customer characteristics can be used and how high the premium can be priced in the pricing schedule are also subject to approval. Fifth, only the largest auto insurers (and not even all of them) offer auto insurance in all 50 states and the District of Columbia (DC). Most insurance companies only offer coverage in a number of states, for example, American Family in 18 states and Mercury in 13. Sixth, following from the previous point, there are big differences in the competitive landscape in each state. Although the five largest companies are present in all states and DC (except Progressive is not present in Massachusetts), they face a different set of competitors in each state and have different market shares. Seventh, not only do market leaders vary by state, but also the number of companies that consumers can choose from is different. For example, residents of Hawaii can pick from 16 companies, consumers in Wyoming from 31, consumers in New York from 47, and consumers in Indiana from 61 of the 100 largest insurance companies.[4]

The characteristics of the US private passenger auto insurance industry are taken into account in my modelling approach. First, the observation that it is a very fragmented industry indicates that it is not enough to model demand for the five largest insurers, but that instead, a much larger set of companies needs to be included. I model demand for 16 of the 20 largest insurance groups.[5] Although it would have been desirable to include all 20 insurance groups, it was not possible for practical reasons: two companies (AAA and USAA) require membership to request price quotes (and purchase insurance). I therefore had to exclude them in the price reconstruction process (see Section 3 and Appendix A for details). Furthermore, the data do not contain enough observations to include the insurer Encompass. Going beyond the 20 largest insurance groups was not possible, as the marketing research company collecting the data focused on this group of insurers. Second, the strict disclosure regulations of insurance premia will be important in my approach to insurance prices (Section 5). Finally, the observation that the set of companies offering auto insurance varies widely from state to state (by size and composition) motivates my approach to let consumers search among and choose from state-specific sets of companies.

[4] The 100 largest companies are a good estimate of the total number of insurance companies because they had a market share of 96.2% in 2007.

[5] One insurance group (AIG) had two private passenger auto insurance companies at the time of my survey (21st Century and AIG). I model demand for these two companies separately.

TABLE 1 Observed Variables

1.	Number of quotes
2.	Identity of companies the respondent got quotes from
3.	Previous and current auto insurance company
4.	Premium paid with current and previous auto insurance company
5.	Demographics: age, gender, marital status, income, education, children under age 18 in the household
6.	Location: zip code, community type (e.g., rural or urban area, suburb)
7.	Number of drivers and drivers under 25 years on the policy
8.	Number of vehicles on the policy and the primary vehicle's year, make, and model
9.	Number of years with current insurance company
10.	Self-assessed credit history
11.	Period with no insurance during last three years
12.	Two or more tickets during last three years
13.	Two or more accidents during last three years
14.	Homeowner insurance with current auto insurance company
15.	Homeowner insurance with other insurance company
16.	Relocated during the past 12 months and, if yes, state previously lived in
17.	Quoting channel (e.g., agent, insurer website)
18.	Psychographic questions
19.	Attitudes toward auto insurance companies
20.	Customer satisfaction measures with current auto insurance company
21.	Advertising recall

3. Data

■ The data come from an insurance shopping study conducted in 2006 and 2007 by a large marketing research company. I observe from which companies consumers got quotes and with which company they signed. This provides information on the number and identity of companies searched and the switching decision. In addition, I observe a nearly complete customer profile containing information on demographics, psychographics, attitudes toward auto insurance companies, advertising recall, drivers, cars, location, past claims history, and other insurance products (see Table 1). Finally, I also have information on purchase prices for all chosen companies. However, to model a consumer's purchase decision conditional on his search as a choice model, I also need the prices for the companies the consumer considered but did not end up choosing. I went through an elaborate process of reconstructing these prices (along with consumers' coverage choices) and refer the reader to Appendix A for details.

□ **Data description.** Consumers get on average 2.96 quotes (including one from their previous insurer) with the majority of consumers collecting two or three quotes (see Figure 1). The average premium with the current insurer is \$592.97 (see Table 2). Table 3 compares the mean characteristics for each respondent type (No Search/No Switch, Search/No Switch, Search/Switch). Consumers who neither search nor switch get as expected only one quote—the one that their previous insurer sends to them; consumers who search, but decide not to switch collect 2.89 quotes on average and consumers who search and switch gather 3.51 quotes. Although there is not much difference in the number of information sources and online quote sites visited across the three respondent types, consumers who search use more methods to obtain quotes. Consumers who neither search nor switch pay the highest average premium (\$660.13), followed by consumers who search, but decide to stay with their previous insurer (\$606.36). Consumers who search and switch pay on average \$551.44.

Table 4 contains information about the composition of consideration sets, market shares, retention and conversion rates, that is, the probability that a company will be chosen conditional on being considered. The left column shows that more than half of the respondents request a quote from Geico, followed by Progressive, Allstate, and State Farm. These four companies have the largest presence with market shares between 12% and 19%. Safeco and GMAC have the smallest

FIGURE 1

DISTRIBUTION OF CONSIDERATION SET SIZES

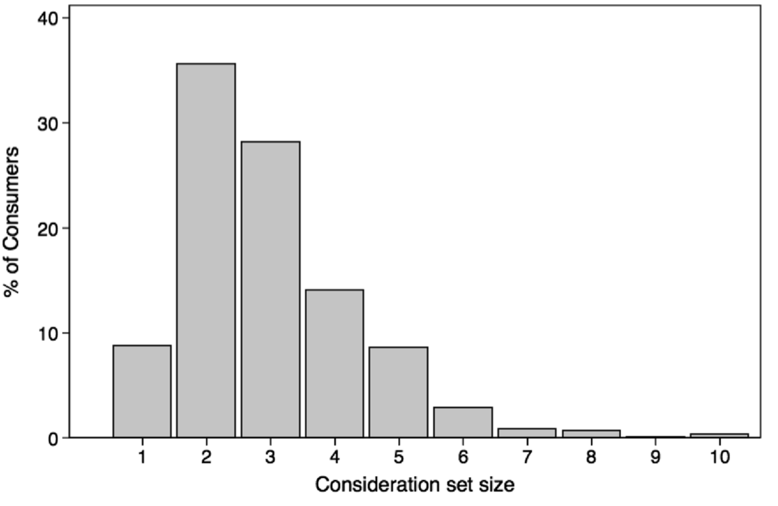


TABLE 2 Descriptive Statistics

	N	Mean	Standard deviation	Minimum	Maximum
Number of quotes	945	2.96	1.38	1	10
Number of information sources	945	2.12	1.28	1	8
Number of methods to obtain a quote	945	2.01	0.90	1	6
Number of online quote sites visited	419	1.14	0.40	0	4
Length of price quote gathering process	879	1.54	1.27	0	12
Length of choosing process	854	1.36	1.27	0	11
Premium for six-months policy with PI	270	756.41	365.10	105	2700
Premium for six-months policy with CI (same sample as PI)	270	554.49	265.90	89	2750
Premium for six-months policy with CI	945	592.97	288.28	74	2750
Number of vehicles with CI	945	1.58	0.64	1	3
Number of drivers with CI	945	1.64	0.59	1	4
Number of years with CI	945	7.07	9.04	0	50
Number of people in the household	927	2.33	1.12	1	8
Number of hours online per week	918	15.21	12.26	0	80
Vehicle year	945	2001.98	4.19	1960	2007
Respondent age	945	45.23	12.94	20	84
From Reconstructed Price Quotes					
Matched premium for six-months policy with PI	945	606.58	280.07	108	1948
Matched premium for six-months policy with PI —same sample as above	270	626.19	266.11	174	1778
Matched premium for six-months policy with CI	945	585.17	227.78	119	2706
Customer Satisfaction					
Billings and payment process	942	8.16	1.77	1	10
Price	945	7.95	1.83	1	10
Interacting with insurer	917	8.24	1.78	1	10
Policy offerings	940	7.93	1.69	1	10
Claims experience	532	8.14	1.90	1	10
Overall experience	943	8.33	1.51	1	10

Notes: PI: Previous Insurer; CI: Current Insurer.

TABLE 3 **Averages Across Customer Types**

	No Search/ No Switch	Search/No Switch	Search/Switch
Number of respondents	56	586	303
Number of quotes	1	2.89	3.51
Number of information sources	2.27	2.00	2.33
Number of methods to obtain a quote	1.20	2.00	2.20
Number of online quote sites visited	1.21	1.13	1.15
Length of price quote gathering process	1.42	1.44	1.75
Length of choosing process	1.07	1.26	1.62
Premium for six-months policy with PI			756.41
Premium for six-months policy with CI	660.13	606.36	551.44
Number of vehicles with CI	1.61	1.60	1.54
Number of drivers with CI	1.73	1.65	1.60
Number of years with CI	7.83	10.14	
Number of people in the household	2.55	2.26	2.43
Number of hours online per week	16.23	14.88	15.73
Vehicle year	2002.93	2001.86	2002.05
Respondent age	42.17	46.90	42.35

Notes: PI: Previous Insurer; CI: Current Insurer.

TABLE 4 **Consideration Set Composition, Market Shares, Retention, and Conversation Rates**

	Considered By % Respondents	Market Share[a]	Retention Rate[a]	Conversion Rate[a]
21st Century	7.91	2.81	81.72	35.51
AIG	20.81	3.96	63.29	18.74
Allstate	36.60	14.16	69.84	38.70
American Family	6.61	2.53	91.03	38.25
Erie	5.00	2.83	96.25	56.66
Farmers	11.86	4.92	79.62	41.46
Geico	53.91	18.41	64.10	34.16
GMAC	5.65	1.60	67.12	28.34
The Hartford	13.98	4.24	87.07	30.35
Liberty Mutual	10.38	4.73	70.44	45.53
Mercury	5.23	2.22	81.07	42.46
MetLife	6.37	2.29	64.51	37.02
Nationwide	11.94	3.35	74.69	28.06
Progressive	46.98	12.42	62.67	26.56
Safeco	4.82	1.68	52.52	33.41
State Farm	34.26	13.18	72.40	38.48
Travelers	7.85	4.51	72.63	57.47

Notes: [a]Measured in percent.

market shares. The overall average retention rate is 74%. Allstate and State Farm have higher retention rates than Geico and Progressive (70% and 72% versus 64% and 63%). The companies with the highest conversion rates are, surprisingly, Erie and Travelers. Among the companies with the lowest conversion rates are not only the companies with the lowest market shares, Safeco and GMAC, but also two companies which have the highest and third-highest market shares, namely, Geico and Progressive. It seems that these two companies are good at getting people to request quotes from them, but not good at converting these quotes into actual purchases. I refer the reader to Appendix A for a more detailed description of the data.

To ensure the representativeness of my data set vis-à-vis the population of consumers purchasing auto insurance, I use representativeness weights provided by the marketing research company to summarize my data and to make predictions. Representativeness weights are weights assigned to each consumer with the goal of creating a data set that is representative of the population with respect to demographics. These weights vary from .45 to 2.06. Results are robust to ignoring representative weights.

□ **Data limitations.** Although the data are well suited to study consumer search and purchase decisions because both are observed by the researcher, together with a rich set of data on demographic, psychographic, and attitudinal variables, the data have their limitations. First, both coverage choices and competitive quotes are not observed in the original data and had to be reconstructed by the researcher (see Appendix A). As additional assumptions had to be made during this reconstruction process, they introduce additional noise in the data. I try to alleviate concerns regarding this issue in a robustness check (see the fourth subsection of Appendix B). Second, the data were self-reported by the consumer after the purchase occasion. Although directly checking the accuracy of the self-reported data is not possible, I compared it to national statistics on average auto insurance premia, on the average number of collected quotes, and several demographic variables, and find my data to be representative. I conclude that, although the data are not without limitations, the benefits of understanding search and switching costs outweigh the costs imposed by the limitations of the data.

4. Model

□ **Main model assumptions.** Before introducing the model, I discuss the main assumptions regarding consumer behavior. In the model, (i) the consumer's search and purchase decisions are conditional on his choice of coverage; (ii) consumers search to resolve uncertainty about prices; and (iii) consumers use a simultaneous search approach.

I describe a consumer's auto insurance policy search and purchase decisions *after* he has decided on the various policy characteristics he would like his insurance policy to have (i.e., coverage levels, etc.). This means that consumers want to buy the same or a very similar insurance policy from each available insurance company. This assumption is necessary because I only observe a consumer's choice of coverage for his current insurer, but not his coverage choice for *each* company a consumer considered separately. Although the assumption of identical or very similar coverages across insurance companies at a purchase occasion is somewhat restrictive, I observe consumers reporting considerable stickiness in their coverage choices. For example, over 93% of consumers in the data state that they kept their coverage choice the same during the last shopping occasion. This assumption is also consistent with previous empirical research where consumers decide which product they want to purchase prior to the shopping occasion and are searching for the price of a product (Mehta, Rajiv, and Srinivasan, 2003; Hong and Shum, 2006; Moraga-Gonzalez and Wildenbeest, 2008) albeit in different categories.

Next, I assume that when searching for auto insurance the main source of a consumer's uncertainty is the price, that is, the premium charged by each provider. Thus, the only search dimension is price. This assumption is motivated by two reasons. First, 47% of the consumers in the data report that learning about prices is their most important reason to shop;[6] and second, insurance premia depend on consumer and policy characteristics. The latter reason has two consequences. On the one hand, auto insurance companies are not able to advertise *specific* prices because there are millions of different auto insurance premia. Insurance companies can only advertise how much consumers save (on average) or emphasize their position as a low-cost auto insurance provider, for example, Geico's "15 minutes could save you 15% or more" or the advertisements on insurers' websites mentioned in Section 1 reinforcing the notion of potential savings and price dispersion in the auto insurance industry. On the other hand, consumers do not know the exact price an auto insurance company is going to charge them *unless* they go through the price quoting process. Thus, price uncertainty from the consumer's perspective is very high in

[6] "Buying or selling a vehicle" was the second most important shopping prompter with a percentage of 7.5.

this industry, and going through the price quotation process is a prerequisite for consumers to be able to purchase an insurance policy. I also find a high level of price dispersion in the data (see the fifth subsection of Appendix B). First, the company-specific mean prices intuitively make sense, as holding everything else constant the same person expects to pay more for the same policy with State Farm than with Geico. Second, the standard deviations are substantial. This implies that there remain factors that I do not observe that might make actual prices differ substiantially from average prices. Consumers have to search to learn the exact premium an insurance company will charge them. By letting consumers search for prices (only), my model is able to capture this primary form of uncertainty in the auto insurance industry.

My last main assumption concerns the type of search process consumers use. I assume consumers search simultaneously when forming their consideration sets. Morgan and Manning (1985) have found that either sequential or simultaneous search (or a combination of both) can be optimal for a consumer. Empirical research has used both types of search processes. For example, the sequential approach has been adopted by Kim, Bronnenberg, and Albuquerque (2010) and the simultaneous search approach appears in Mehta, Rajiv, and Srinivasan (2003). In a recent working paper, Honka and Chintagunta (2014) show that the search method consumers use is identified when consideration sets and actual prices are observed. Further, they also show, using the same data as in this article, that consumers use the simultaneous search method when shopping for auto insurance. Thus, I concentrate on the simultaneous search case.

□ **Model development.** Formally, there are $i = 1, \ldots, N$ consumers who live in $m = 1, \ldots, M$ states with a different number and composition of insurance companies in each market. I view each state as a market. Across all markets there are $j = 1, \ldots, J$ insurance companies; within a market there are $j = 1, \ldots, J_m$ insurance companies. The set of available auto insurers in state m is denoted by Ψ_m. Consumer search costs are denoted by c_i and the number of searches that a consumer conducts is denoted by k. The set of companies a consumer searches is denoted by S_i and the set of companies a consumer does not search is denoted by $\bar{S}_i$. The companies a consumer searches and his previous insurer form the consumer's consideration set C_i, that is, $C_i = S_i \cup \{j_{I_{ij,t-1}}\}$, where $j_{I_{ij,t-1}}$ denotes the previous insurer so that $\Psi_m = C_i \cup \bar{S}_i$. Consumer $i's$ indirect utility for company j is given by

$$u_{ij} = \alpha_{ij} + \beta_i I_{ij,t-1} + \gamma p_{ij} + X_{ij}\rho + W_i\phi + \epsilon_{ij}. \tag{1a}$$

with

$$\beta_i = \tilde{\beta} + Z_i\kappa. \tag{1b}$$

ϵ_{ij} captures a component of the utility that is observed by the consumer, but not the researcher. I assume ϵ_{ij} follow an EV Type I distribution with location parameter 0 and scale parameter 1. α_{ij} are consumer-specific brand intercepts. I define $\alpha = (\alpha_1, \ldots, \alpha_J)$ and assume that α follows a MVN distribution with mean $\bar{\alpha}$ and covariance matrix Σ_α. β_i captures consumer inertia. $I_{ij,t-1}$ is a dummy variable indicating whether company j is consumer $i's$ previous insurer. I control for observable heterogeneity in consumer inertia β_i: Z_i contains demographic factors (e.g., age, gender), psychographic factors (e.g., loyalty, interest in finance), and customer satisfaction with the previous insurer (e.g., with claims process, pricing). Note that as observed heterogeneity interacts with $I_{ij,t-1}$, it plays a role in the conditional choice decisions. In interpreting the results, I attribute the part of customer inertia associated with the constant $\tilde{\beta}$, demographic and psychographic factors to customer switching costs, and the part of customer inertia associated with customer satisfaction to customer satisfaction.[7] γ captures a consumer's price sensitivity and p_{ij} denotes the price charged by company j. Note that—in contrast to the consumer packaged goods

[7] I do so by calculating the total effect of consumer inertia and the effect associated with the constant $\tilde{\beta}$, demographic and psychographic factors. The difference between these two effects is the part of inertia associated with customer satisfaction.

industry—in the auto insurance industry, prices depend on consumer characteristics. As common in the literature on search, I assume that, even though consumers do not know the prices each specific company would charge them, they know the distributions of prices present in the market. I assume prices p_{ij} have an EV Type I distribution with location parameter η_{ij} and scale parameter μ (as in Mehta, Rajiv, and Srinivasan, 2003).[8] Given that consumers know the distributions of prices in the market, they know η_{ij} and μ. I describe in detail in Section 6 how I estimate the price distributions conditional on consumer characteristics.

X_{ij} is a vector of product- and consumer-specific attributes which include observed consumer attitudes toward auto insurance companies in two areas, namely, proven reliability and out-of-the-box character of an insurance company and an interaction term between advertising spending and recall. "Recall" captures consumer $i's$ self-reported recall of having seen advertisements from insurer j during the insurance shopping period. By interacting company-specific advertising spending with consumer-specific advertising recall, I ensure that only the advertising consumer i is aware of enters his utility function.[9] Note that these variables are both consumer- and company-specific. Finally, W_i contains demographic factors (e.g., age, marital status), psychographic factors (e.g., loyalty, interest in finance, etc.) and regional fixed effects (e.g., New England, Mid-Atlantic) that are common across j. Although these factors drop out of the conditional choice decision, they may play a role in the search and consideration decisions.

I assume consumers know all company characteristics except for prices. Searching for prices is costly; therefore, consumers only collect price information from a limited number of companies. Consumers do not search their previous insurer as insurance companies automatically send their customers renewal notices and, thus, consumers receive a free quote from their previous insurer.[10] So the quote from the previous insurer can be seen as a consumer's "fall-back option" because the no-purchase option does not exist in this market.

Before collecting price information, consumers have to decide which companies to search. For the sequential search model, Weitzman (1979) showed that the optimal company selection strategy, that is, the answer to the question which companies to search, is to calculate each company's reservation utility, rank them in decreasing order, start with the top-ranked company, and work down. Such a general result does not exist for the simultaneous search model. In the working paper version of their article (Chade and Smith, 2006), Chade and Smith (2005) show that a simple optimal selection strategy for simultaneous search exists if there is first-order stochastic dominance among the company-specific distributions over which the consumer is searching. In that case, the consumer's optimal selection strategy is to calculate the expected utilities, rank them in decreasing order, start with the top-ranked company, and work his way down. For a second special case, namely, second-order stochastic dominance among the company-specific distributions, Vishwanath (1992) shows that—identical to Weitzman's (1979) result for the sequential search model—the optimal strategy for simultaneous search is for the consumer to rank the options according to the reservation utilities and work his way down. Note that the ordering in Weitzman (1979) and Vishwanath (1992) is done according to reservation utilities, whereas in Chade and Smith (2005), it is done according to expected utilities.

I am not aware of a simple strategy which describes the optimal selection strategy in the absence of first- or second-order stochastic dominance for the simultaneous search model. Here is some intuition for why a general solution is difficult to find: choosing a set of companies to search is similar to a portfolio problem where each option is characterized by a mean and

[8] $f(x) = \mu \exp(-\mu(x-\eta)) \exp(-\exp(-\mu(x-\eta)))$ and $F(x) = \exp(-\exp(-\mu(x-\eta)))$ with location parameter η and scale parameter μ. Mean is $\eta + \frac{e_c}{\mu}$ and variance $\frac{\pi^2}{6\mu^2}$ where e_c is Euler constant (Ben-Akiva and Lerman, 1985).

[9] The results are robust to different specifications of how advertising enters the utility function such as advertising spending only, advertising recall only, both main effects, and both main effects together with the interaction effect.

[10] In the data, all consumers get automatic renewal offers from their previous insurers. Even if I observed some consumers not getting renewal notices, that is, the insurance company refusing to renew a policy, that would be the result of the company's, and not the consumer's decision.

variance. Suppose one has to make a decision between two options: the first option has a lower mean, but a higher variance than the second option, that is, the expected value (utility) from the first option is lower, but there is also a higher chance of getting an outlier with a high value (utility) than with the second option. How should a consumer weigh the lower mean against the higher variance? To circumvent this problem, I assume first-order stochastic dominance among the price belief distributions and use the optimal selection strategy suggested by Chade and Smith (2005). I assume a specific form of first-order stochastic dominance, namely, that the price belief distributions have consumer- and company-specific means but the same variance across all companies.

I will now describe the remainder of the model from the perspective of a consumer. Note that the consumer makes the decisions of which and how many companies to search at the same time. For expository purposes, I first discuss the consumer's decision of which companies to search followed by the consumer's decision of how many companies to search. Both decisions are jointly estimated. In the previous paragraphs, I established that a consumer's decision regarding which companies to search depends on the expected indirect utilities (EIU; Chade and Smith, 2005) where the expectation is taken with respect to the characteristic the consumer is searching for—in this case, prices. So consumer $i's$ EIU is given by

$$E\left[u_{ij}\right] = \alpha_{ij} + \beta_i I_{ij,t-1} + \gamma E\left[p_{ij}\right] + X_{ij}\rho + W_i\phi + \epsilon_{ij}, \tag{2}$$

Consumer i observes these EIUs for every company in his market (including ϵ_{ij}). To decide which companies to search, consumer i ranks all companies other than his previous insurance provider (because the consumer gets a free renewal offer from the previous insurer) according to their EIUs (Chade and Smith, 2005) and then picks the top k companies to search. R_{ik} denotes the set of top k companies consumer i ranks highest according to their EIU. For example, R_{i1} contains the company with the highest expected utility for consumer i, R_{i2} contains the companies with the two highest expected utilities for consumer i, etc.

To decide on the number of companies k a consumer searches, the consumer calculates the net benefit of all possible search sets *given the ranking of EIUs*, that is, if there are N companies in the market, the consumer can choose among $N-1$ search *sets* (one free quote comes from the previous insurer). A consumer's benefit of a searched *set* is then given by the expected *maximum* utility among the searched brands. Given the EV distribution of prices, the maximum utility has also an EV distribution

$$\max_{j \in R_{ik}} u_{ij} \sim EV\left(\frac{1}{b}\ln\sum_{j\in R_{ik}}\exp\left(ba_{ij}\right), b\right), \tag{3}$$

with $a_{ij} = \alpha_{ij} + \beta_i I_{ij,t-1} + \gamma\eta_{ij} + X_{ij}\rho + W_i\phi + \epsilon_{ij}$ and $b = \frac{\mu}{\gamma}$. If we further define $\tilde{a}_{R_{ik}} = \frac{1}{b}\ln\sum_{j\in R_{ik}}\exp(ba_{ij})$, then the benefit of a searched set is given by

$$E\left[\max_{j\in R_{ik}} u_{ij}\right] = \tilde{a}_{R_{ik}} + \frac{e_c}{b}, \tag{4}$$

where e_c, denotes the Euler constant. The consumer picks S_{ik}, which maximizes his net benefit of searching denoted by $\Gamma_{i,k+1}$, that is, the expected maximum utility among the considered companies minus the cost of search, given by

$$\Gamma_{i,k+1} = E\left[\max_{j\in R_{ik}\cup\left\{j_{I_{ij,t-1}}\right\}} u_{ij}\right] - kc_i. \tag{5}$$

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 kc_i on search costs and has $k+1$ companies in his consideration set.

Consumers can be heterogeneous in both preferences and search costs. Consumer-specific effects in *both* the utility function and search costs are not identified because of the linear relationship between utilities and search costs in equation (5). If we increase, for example, the effect of a demographic factor in the utility function and decrease its effect on search costs by an appropriate amount and the benefit of a consideration set, $\Gamma_{i,k+1}$, would remain the same. In the empirical specification, I therefore control for observed and unobserved heterogeneity in the utility function and for quoting channels (e.g., agent, insurer website) in search costs.

This concludes the description of how a consumer forms his consideration set. Once a consumer has formed his consideration set and received all price quotes he requested, all price uncertainty is resolved. Both the consumer and the researcher observe prices. The consumer then picks the company with the highest utility among the considered companies, that is,

$$j = \arg\max_{j \in C_i} \; u_{ij}, \tag{6}$$

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

5. Estimation

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

(i) Whereas the consumer knows the distributions of prices in the market, the researcher *estimates* the parameters defining the price distributions;
(ii) Whereas the consumer knows his psychographic factors and brand preferences, the researcher *estimates* the psychographic and observed brand preference factors;
(iii) Whereas the consumer knows each company's position in the EIU ranking, the researcher only partially observes the ranking by observing which companies are being searched and which ones are not being searched;
(iv) In contrast to the consumer, the researcher does not observe α_{ij} and ϵ_{ij}.

I tackle the first two points by integrating over the empirical distributions of the price, psychographics, and observed brand preferences parameters given the sampling error associated with estimating these parameters (McFadden, 1986). To address the third issue, I point out that partially observing the ranking contains information that allows me to estimate the composition of consideration sets. Because the consumer ranks the companies according to their EIU and searches only the highest ranked companies, the researcher knows from observing which companies are searched that the EIUs among all the searched companies have to be larger than the EIUs of the nonsearched companies or, to put it differently, that the minimum EIU among the searched companies has to be larger than the maximum EIU among the nonsearched companies, that is,

$$\min_{j \in S_i} (E[u_{ij}]) \geq \max_{j' \notin S_i} (E[u_{ij'}]). \tag{7}$$

As a consumer decides simultaneously which and how many companies to search, the following condition has to hold for any searched set:

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

that is, the minimum EIU among the searched brands is larger than the maximum EIU among the nonsearched 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'.

Finally, I account for the fact that the researcher does not observe α_{ij} and ϵ_{ij} by integrating over their distributions. Recall that I assumed that $\alpha \sim MVN(\bar{\alpha}, \Sigma_\alpha)$ where $\bar{\alpha}$ and Σ_α contain parameters to be estimated and $\epsilon_{ij} \sim EV\,Type\,I\,(0, 1)$. Then the probability that a consumer picks a consideration set Υ is given by

$$P_{i\Upsilon|\alpha,\epsilon} = \Pr\Big(\min_{j \in S_i}\big(E\left[u_{ij}\right]\big) \geq \max_{j' \notin S_i}\big(E\left[u_{ij'}\right]\big) \quad \cap \quad \Gamma_{i,k+1} \geq \Gamma_{i,k'+1} \qquad \forall k \neq k'\Big). \tag{9}$$

Note that the quote from the previous insurer directly influences the consumer's choice of the size of a consideration set. A consumer renews his insurance policy with his previous provider if the utility of doing so is larger than the expected net benefit $\Gamma_{i,k+1}$ of any number of searches.

Next, I turn to the purchase decision given consideration. The consumer's choice probability conditional on his consideration set is

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

where u_{ij} now contains the quoted prices. Note that there is a selection issue: given a consumer's search decision, ϵ_{ij} do not follow an EV Type I distribution and the conditional choice probabilities do not have a closed-form expression. The consumer's unconditional choice probability is given by

$$P_{ij|\alpha,\epsilon} = P_{i\Upsilon|\alpha,\epsilon} P_{ij|\Upsilon,\alpha,\epsilon}, \tag{11}$$

In summary, the researcher estimates the price distributions, only partially observes the utility rankings, and does not observe α_{ij} and ϵ_{ij} in the consumer's utility function. Accounting for these issues, I derived an estimable model with consideration set probability given by (9) and the conditional and unconditional purchase probabilities given by (10) and (11). Parameters are estimated by maximizing the joint likelihood of consideration and purchase given by

$$L = \prod_{i=1}^{N} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \left(\prod_{l=1}^{L} \prod_{j=1}^{J} P_{i\Upsilon|\alpha,\epsilon}^{\vartheta_{il}} P_{ij|\Upsilon,\alpha\epsilon}^{\delta_{ij}} \right) f(\alpha) f(\epsilon)\, d\alpha d\epsilon, \tag{12}$$

where ϑ_{il} indicates the chosen consideration set and δ_{ij} the chosen company. Neither the consideration set nor the conditional purchase probability have a closed-form solution. I therefore use a simulation approach to calculate them. In particular, I simulate from the distributions of α_{ij} and ϵ_{ij}. A crude way to calculate the consideration set and conditional purchase probabilities would be by counting the proportion of times that the optimality conditions in equations (9) or (10) are satisfied. However, this would result in lumpy probabilities which cannot be optimized using common optimization routines and would require non-gradient based methods or a very large number of draws. Therefore, I use a kernel-smoothed frequency simulator (McFadden, 1989) in the estimation and smooth the probabilities using a multivariate scaled logistic CDF (Gumbel, 1961):

$$F(w_1, \ldots, w_T; s_1, \ldots, s_T) = \frac{1}{1 + \sum_{t=1}^{T} \exp(-s_t w_t)} \qquad \forall\, t = 1, \ldots, T, \tag{13}$$

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

This estimator is implemented in four steps. First, I take Q draws for α_{ij} and ϵ_{ij} for each consumer/company combination. Second, for each α_{ij} and ϵ_{ij} draw, I calculate w_t^q for the consideration set and conditional purchase probabilities. For example, $w_{1|\alpha,\epsilon}^q = u_{ij} - \max(u_{i,j'}) \quad \forall j \neq j'$, and $\forall j, j' \in C_i$ for the conditional purchase probabilities. Third, I calculate the smoothed consideration and purchase probabilities using (13). For example, $P_{ij|\Upsilon,\alpha,\epsilon}^q = \frac{1}{1+\exp\left(-s_1 w_{1|\alpha,\epsilon}^q\right)}$ for the conditional purchase probabilities. Finally, I average the *un*conditional purchase probabilities across all Q draws for α_{ij} and ϵ_{ij}. In the estimation, I use a scaling factor of $s_1 = s_2 = 15$ and take $Q = 50$ draws.

I test the performance of my estimation approach by simulating data on search set and purchase decisions for 1000 consumers. Consumers can choose among six brands with the first search being free. I take 50 draws from the distribution of the error term and replicate the simulation 50 times. The true parameter values and the simulation study results are shown in Table 5. The true values are recovered quite well. I provide further details on the estimation approach and the simulation study in the first subsection of Appendix B.

TABLE 5 Simulation Study Results

	True Values	Estimates	Standard Error
Brand Intercept 1	−2.00	−1.99	(.14)
Brand Intercept 2	−1.60	−1.72	(.14)
Brand Intercept 3	−2.10	−2.07	(.13)
Brand Intercept 4	−2.40	−2.27	(.13)
Brand Intercept 5	−1.40	−1.59	(.15)
Brand Intercept 6	−1.80	−1.77	(.15)
Advertising	.50	.47	(.03)
Price	−1.00	−0.96	(.04)
Search cost	.30	.28	(.03)
Loglikelihood		−3545.06	

TABLE 6 Example

	Prices in $	
	Consumer 1	Consumer 2
Company 1	500	2000
Company 2	400	2100
Company 3	550	1900
Company 4	600	1950
Average price	512.50	1987.50

□ **Estimation of consumer price beliefs.** The model states that before collecting quotes prices are unknown to consumers but that consumers have beliefs about prices. Specifically, I assume that consumers have rational expectations about prices and know the company-specific distributions of prices present in the market. Previous literature (e.g., Mehta, Rajiv, and Srinivasan, 2003; Hong and Shum, 2006; Moraga-Gonzalez and Wildenbeest, 2008) has deemed this assumption reasonable and estimated the empirical price distributions using prices present in the market. I cannot directly take this approach as it would lead to unreasonable price expectations as insurance premia—in contrast to most other product prices—depend on consumer and policy characteristics (e.g., coverage choices, payment arrangements, etc.). Table 6 shows a simple example of a market with two consumers and four companies. Consumer 1 wants to purchase auto insurance for himself and his one car, whereas consumer 2 wants to buy a policy for four cars and three drivers, one of whom is under the age of 25. Both consumers get a quote from the same set of companies for the same coverage. The average price in the market for a 6-months policy is \$1250. Using the market-wide average price as the expected price for all consumers would neither make sense for consumer 1 nor consumer 2. Instead, I calculate consumer-specific price expectations by accounting for consumer and policy characteristics. In the example in Table 6 this amounts to calculating separate average prices for consumer 1 (\$512.50) and consumer 2 (\$1987.50). The different average price levels are entirely due to consumer and policy characteristics, that is, consumer 2 having more drivers with different characteristics and more cars on the insurance policy, and have to be controlled for when price expectations are estimated.

To reflect consumers' knowledge of the prices present in the market before the search, I use only the prices charged by the previous insurers of consumers in the sample. I assume prices have an EV Type I distribution and regress all prices charged by previous insurers (pooled across consumers) on personal and policy characteristics as well as company-specific fixed effects, that is,

$$p_{ij} \sim EV\left(\eta_{ij};\mu\right) \quad with \ \ \eta_{ij} = D_{ij}\varsigma, \tag{14}$$

where ς is a coefficient vector and D_{ij} contains the personal and policy characteristics and company-specific fixed effects. Note that the personal and policy characteristics that define insurance prices fall under the Freedom of Information Act (FOIA) and are publicly known. As described previously, I have data on almost all of these characteristics. I use the consumer- and company-specific expected prices from equation (14) as price expectations when estimating the consideration set probabilities in the model (equation (9)). Note that, within a consumer, the expected prices only vary by the company-specific fixed effects.

I estimate the model in two steps. First, I estimate the price beliefs. I then estimate the model as described previously. This two-step estimation approach for the price process and the main model is similar to previous literature on consumer search such as Mehta, Rajiv, and Srinivasan (2003), Hong and Shum (2006), and Moraga-Gonzalez and Wildenbeest (2008) and is also common in the literature on dynamic demand estimation (e.g., Erdem, Imai, and Keane, 2003; Erdem, Keane, and Sun, 2008).

□ **Comparison with previous approaches.** In the search literature, this article is closely related to Mehta, Rajiv, and Srinivasan (2003), Kim, Bronnenberg, and Albuquerque (2010), and De los Santos, Hortaçsu, and Wildenbeest (2012). All three articles explicitly acknowledge and model search as the way consumers form their consideration sets. Neither Mehta, Rajiv, and Srinivasan (2003) nor Kim, Bronnenberg, and Albuquerque (2010) observe the search process, but the latter article observes the outcome of search at the aggregate level in the form of view rankings. In contrast, De los Santos, Hortaçsu, and Wildenbeest (2012) observe the sequence of searches for each consumer. All three articles quantify search costs and estimate the size and composition of consideration sets. In my data, I observe the set of companies a consumer considered and his purchase decision at the individual level. Contrary to Kim, Bronnenberg, and Albuquerque (2010), I assume consumers search simultaneously. This article differs from Mehta, Rajiv, and Srinivasan (2003) and De los Santos, Hortaçsu, and Wildenbeest (2012) in the estimation approach.

Similarly to my approach, Mehta, Rajiv, and Srinivasan (2003) explicitly model the search process that leads to the formation of consideration sets, although they use only choice data. Intuitively speaking, they use a choice model to describe a consumer's decision of consideration set. They enumerate all possible consideration sets (by size and composition) and assume that the consumer picks the one which provides him with the largest benefit (net of cost) by fitting the choice model. This approach is only feasible for a small set of alternatives because the number of consideration sets dramatically increases with the number of alternatives.[11] The reason for why this happens is a well-documented curse of dimensionality in simultaneous search models (Chiang, Chib, and Narasimhan, 1999; Kim, Bronnenberg, and Albuquerque, 2010). Previous research has usually overcome this challenge by focusing on categories with a few dominant (by market share) brands in the empirical applications. For example, Mehta, Rajiv, and Srinivasan (2003) apply their model to the liquid detergent and ketchup categories, where the largest four brands have a combined market share of 81% and 92%, respectively. The exclusive focus on markets with a few dominant brands limits the applicability of the choice model estimation approach in empirical settings, where many fragmented markets can be found. For example, for the auto insurance industry, I would need to include at least 17 companies to achieve a combined market share of more than 70% similar to previous research (e.g., Mehta, Rajiv, and Srinivasan, 2003; Zhang, 2006). With such a large number of companies, implementing the choice model approach suggested by Mehta, Rajiv, and Srinivasan (2003) is not feasible.

By using the theory based on Chade and Smith (2005) and the associated EIU ranking, I overcome the curse of dimensionality and effectively reduce the number of search sets from $2^N - 1$ to N. This allows me to estimate consideration set probabilities in categories with a large

[11] Given knowledge of the purchased brand, some of the combinations can be eliminated as the purchased brand always has to be part of the consideration set.

number of brands. Note that equation (9) is flexible enough to estimate probabilities of all possible combinations of consideration set sizes and compositions. Suppose there are four brands in a market denoted by A, B, C, and D; a consumer considers brands A and B and purchases brand A. Assuming the considered brands are observed and using the approach suggested by Mehta, Rajiv, and Srinivasan (2003), I would fit a choice model with four possible outcomes (AB, ABC, ABD, and ABCD) where the consumer chooses one of these outcomes.[12] Using my approach, I can calculate consideration set probabilities in markets with any number of brands as the joint probability of only *two* events: (i) that the minimum EIU among the considered brands is larger than the maximum EIU among the nonconsidered brands and (ii) that the consideration set of size two (which contains the two brands with the largest EIUs, as all brands are ordered according to their EIUs,) provides the consumer with a larger net benefit than a consideration set of any other size. Thus, my approach is able to predict any consideration set size and composition combination and to do so *independently* of the number of alternatives by describing the probability of observing a consideration set as the joint probability of two events.

The additional flexibility of my approach does come at some cost. First, I need to make the assumption that search costs are identical across companies. This represents a limitation of my approach and prevents me from capturing differences in search costs across insurance companies resulting from, for example, more or less user-friendly online quoting websites. Second, despite the EV Type I distribution of ϵ_j, there exists no closed-form solution for the expression in equation (9). I solve this problem by using a kernel-smoothed frequency simulator (McFadden, 1989) which I describe in the first subsection of Appendix B.

Another difference from some of the previous research is worth mentioning. The models suggested by Mehta, Rajiv, and Srinivasan (2003) and Kim, Bronnenberg, and Albuquerque (2010) do not have an error term which represents a part of the utility function that is known to the consumer but unknown to the researcher.[13] Indeed, both articles would not be able to separately identify an error term from consumer search costs. For example, Kim, Bronnenberg, and Albuquerque (2010) would not be able to differentiate whether a consumer stopped searching because of the level of his search costs or because of information about the brand that is not observed by the researcher if an error term was added to the utility function in their sequential search model. This represents a limitation of previous research, which I am able to overcome because I observe the size of a consumer's consideration set.

6. Identification

■ In this section, I provide an informal discussion of the model identification. The set of parameters to be estimated θ is given by $\{\bar{\alpha}, \Sigma_\alpha, \gamma, \rho, \beta_i, \phi, c\}$. For the purpose of this discussion, I split θ into $\theta_1 = \left\{\bar{\alpha}_1 - \bar{\alpha}_J, \ldots, \bar{\alpha}_{,J-1} - \bar{\alpha}_J, \gamma, \rho, \beta_i\right\}$ and $\theta_2 = \{\Sigma_\alpha, \bar{\alpha}_J, \phi, c\}$. Using choice data alone, θ_1 could be identified. Observing consumers' consideration sets allows me to additionally identify θ_2.

The identification of the θ_1 parameters is standard. With a data set where the researcher observes consumers making a choice among several alternatives, the differences between the brand intercept means and the base brand intercept mean are identified together with preferences for other attributes. Even though I have only cross-sectional data on consumer choices, the additional data containing the identity of the previous insurance provider, that is, lagged choice, allows me to identify consumer inertia β_i. Previous research (e.g., Dubé, Hitsch, and Rossi, 2010) identified switching costs from within consumer persistence in choice over time after controlling for consumer heterogeneity. My identification approach for switching costs differs

[12] If consideration sets are not observed and Mehta, Rajiv, and Srinivasan's (2003) approach is used, eight outcomes are possible (A, AB, AC, AD, ABC, ABD, ACD, ABCD).

[13] Consumers search to resolve uncertainty about the unknown component of their utility e_{ij} in Kim, Bronnenberg, and Albuquerque (2010). Thus, from a modelling perspective, searching for e_{ij} is equivalent to searching for prices as in Mehta, Rajiv, and Srinivasan (2003) or in this article, and not a classic error term.

from previous research in one respect: whereas previous research has attributed all consumer persistence in choice over time to switching costs, I take a more nuanced approach and decompose inertia into two components. The first component consists of consumer inertia stemming from customer satisfaction, which I call satisfaction-based inertia, and the second component consists of consumers being passively inertial, which I interpret as consumer switching costs.

Now, I turn to the identification of θ_2. Unobserved heterogeneity in brand preferences Σ_α is identified from consumer behavior that is inconsistent with the Independence of Irrelevant Alternatives (IIA) characteristic of the conditional choice model. Observing consumers' consideration sets allows me to rule out that non-IIA consumer behavior is due to search costs.

Intuitively speaking, the size of the consideration set will pin down search costs. I 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. For example, suppose it is optimal for a consumer to search once if his search costs lie between three and five, twice if his search costs lie between one and three, and three times if his search costs lie between zero and one. Then by observing a consumer searching twice, I know that his search costs must lie between one and three. Beyond the fact that a consumer's search cost lies within this range, which rationalizes searching a specific number of times, the variation in the 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 after accounting for the EV Type I distribution of the error term and unobserved heterogeneity in brand preferences.

Though consumers have to purchase auto insurance, that is, no purchase is not an option, the fact that consumers have a "fall-back option" (the previous insurer) allows me to identify the base brand intercept mean $\bar{\alpha_J}$. So whereas search costs are pinned down by the average number of searches, the base brand intercept mean is identified by the search or no search decision. This also means that, if there was a "fixed" component of the search cost that did not vary by the number of searches, this fixed cost would not be separately identified from the base brand intercept mean.

The effects of consumer characteristics that do not vary across companies ϕ are identified by consumers with different levels of each characteristic searching more than others. For example, suppose married consumers search on average more companies than single consumers. Then—given that the search cost coefficient is identified by the average number of search across *all* consumers—married consumers must have a larger benefit of searching, that is, a higher utility for insurance, than single consumers. Thus, I would expect a positive coefficient for married consumers in the utility function.

7. Results

□ **Consumer price beliefs.** Section 5 established that insurance prices comprise personal and policy characteristics and that one needs to control for these when estimating price beliefs. Table 7 shows the parameter estimates of the EV Type I distribution for prices where the location parameter is a function of various relevant characteristics, such as a consumer's personal characteristics (age, gender, marital status, etc.), the other drivers on this policy, the insured cars (model age, make, and class), past tickets and accidents, coverage choices, discounts he might receive from having multiple insurance policies with his current auto insurer, his location (that is, state and community type), and company-specific fixed effects. Most coefficients have the expected signs and reasonable magnitudes. For example, insuring a second vehicle costs about \$135 for a 6-months policy and having two or more accidents makes an insurance policy about \$190 more expensive. I conducted a likelihood ratio test and can reject the null model in which only location and scale parameters are estimated (and the location parameter is not a function of observable characteristics) at $p < .001$.

The scale parameter is constant and substantial with 1.4517. This indicates that, even after controlling for price determinants in the location parameter, there remains a substantial proportion

TABLE 7 Price Distribution

	Estimate	Standard Error		Estimate	Standard Error
Location Parameter			*Location Parameter*		
Constant	4.6501***	(.6695)	21st Century	−.7351#	(.3945)
Male	−.1633	(.1322)	AIG	−.3323	(.3510)
Married	.1069	(.2573)	Allstate	.0323	(.2986)
Divorced/Separated	−.0345	(.2373)	American Family	−1.4593***	(.4086)
Widowed	1.2789*	(.5829)	Erie	−1.5574***	(.4233)
Domestic partnership	.3531	(.2985)	Farmers	−.8074*	(.3438)
Age	−.0041	(.0057)	Geico	−1.1550***	(.2894)
Driver under 25 years	.8572**	(.3043)	GMAC	.2993	(.4532)
Two vehicles	1.6260***	(.1613)	The Hartford	−1.0299**	(.3578)
Three vehicles	2.4145***	(.2745)	Liberty Mutual	.0113	(.3257)
Two drivers	−.0889	(.2191)	Mercury	−.2724	(.4279)
Three drivers	1.0885**	(.3909)	MetLife	−.1436	(.4346)
Four drivers	1.3607	(.8741)	Nationwide	−.3807	(.3354)
Medium city suburb	−.0839	(.2088)	Progressive	−.5688#	(.3105)
Large city suburb	.4570*	(.2091)	Safeco	−.6217	(.5266)
Urban area	.4576#	(.2350)	Travelers	.2388	(.3712)
Home owner insurance with CI	−.1831	(.1479)	Chosen coverage	yes	
Other insurance with CI	−.2938*	(.1466)	State	yes	
Two or more accidents	1.7930***	(.4757)	Make*class	yes	
Two or more tickets	.9021***	(.3256)			
Model age	−.0758***	(.0175)	*Scale Parameter*		
			Constant	1.4517***	(.0774)
Fit Statistic					
Loglikelihood	−1,804.70				

Notes: Prices are measured in \$100. CI: Current Insurer.
***$p < .001$, **$p < .01$, *$p < .05$, #$p < .10$.

of variation in prices that is unexplained.[14] This is an expected result because, if characteristics completely explained prices, consumers would have no need to search as they would be able to perfectly predict the prices each insurance company would charge them. The fact that there is unexplained variation in prices is what motivates consumers to search. An example of a characteristic that might be related to the unexplained proportion of prices is a consumer's social security number (SSN). Insurance companies use them to learn a consumer's credit score and set insurance prices accordingly. Consumers might not know their credit score and therefore not know the price an insurance company is going to charge them.

A concern of using estimates from a regression based on premia from considered (previous insurers) companies is selection. In the second and third subsection of Appendix B, I present two alternative robustness checks. Based on those checks, I conclude that selection does not appear to be a concern in the data.

□ **Results from the proposed model.** Now, I turn to the parameter estimates of the model of search and purchase. Table 8 shows the results for two different model specifications. Model 0 shows the results for the basic model with brand intercepts, price, advertising, inertia, and search costs. In Model 1, I additionally allow for unobserved heterogeneity in brand preferences. All but one parameter are significant in Models 0 and 1. Note that I estimate search costs $c = \exp(\tau)$ and consumer inertia $\beta = \exp\left(\tilde{\beta}\right)$, and report τ and $\tilde{\beta}$ in the tables. To translate search cost and inertia from utils into dollars, I divide the corresponding parameter by the price coefficient. I find search costs of \$41.81 in Model 0 and \$36.08 in Model 1. The value of inertia in Model 0

[14] I find similar results when fitting a hedonic pricing regression using the same data and model: the R^2 of that regression is .69, indicating substantial residual price variation (see the fifth subsection of Appendix B).

TABLE 8 Models 0–1

	Model 0		Model 1			
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Brand Preferences				μ_α		σ_α
21st Century	−1.9503***	(.1747)	−2.2819***	(.2054)	.0310***	(.0053)
AIG	−1.6966***	(.1790)	−1.6916***	(.2010)	.2019***	(.0340)
Allstate	−2.1608***	(.1861)	−1.9015***	(.2438)	.0870***	(.0155)
American Family	−1.1148***	(.2032)	−1.7739***	(.4417)	.3563***	(.0897)
Erie	−1.9705***	(.2185)	−1.9429***	(.2775)	.1391**	(.0482)
Farmers	−1.7472***	(.1670)	−2.0885***	(.1965)	.1653***	(.0328)
Geico	−3.0809***	(.2434)	−2.6713***	(.3567)	.3284***	(.0732)
GMAC	−2.1101***	(.1975)	−2.3404***	(.3088)	.4790***	(.0707)
The Hartford	−1.7016***	(.1668)	−1.8203***	(.2342)	.6273***	(.0755)
Liberty Mutual	−1.4740***	(.1682)	−1.7661***	(.2225)	.8731***	(.1764)
Mercury	−2.2090***	(.2140)	−2.4226***	(.2288)	.7061***	(.1753)
MetLife	−2.2233***	(.3625)	−2.3319***	(.3375)	.6306***	(.1083)
Nationwide	−2.3431***	(.1689)	−2.0743***	(.2504)	.7191***	(.1233)
Progressive	−2.2231***	(.2144)	−2.0657***	(.2959)	1.1018***	(.2753)
Safeco	−2.6219***	(.1836)	−2.8472***	(.5316)	.5090***	(.0843)
State Farm	−2.3379***	(.1760)	−2.0368***	(.2123)	.6505	(2.1388)
Travelers	−1.8086***	(.1833)	−2.0338***	(.1897)	.9832***	(.1344)
Other Parameters						
Price	−.3978***	(.0232)	−.3424***	(.0177)		
Recall*advertising	.1677***	(.0400)	.1280***	(.0386)		
Inertia	.2908***	(.0471)	.4870***	(.0435)		
Search cost	−1.7938***	(.2437)	−2.0912***	(.4406)		
Fit Statistics						
Loglikelihood	−3465.17		−3214.85			
AIC	6972.33		6777.69			
BIC	7074.21		7621.80			

Notes: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.
Prices are measured in \$100. Advertising is measured in \$10,000,000.
$^{***}p < .001$, $^{**}p < .01$.

is \$336.22 and \$475.30 in Model 1. I conclude that controlling for unobserved heterogeneity in brand preferences is important in my model, especially for the estimation of consumer inertia.

In Model 2 (Table 9), I further control for observed brand preferences, demographic and psychographic factors, regional fixed effects, and let search costs vary with quoting channels and customer inertia vary with age, gender, income, education, psychographic factors, and satisfaction levels.[15] In interpreting the results, I will concentrate on this model. The mean brand preferences are not significantly different from 0 for all companies, but the standard deviations of the brand preferences are significant for all but two companies (Farmers and State Farm). Further, the amount of unobserved heterogeneity as reflected in the standard deviations of the brand intercepts does not necessarily decrease after the inclusion of observed heterogeneity. Although I report only the means and standard deviations in Table 9, I estimated a full covariance matrix and find the brand preferences for Geico, Progressive, and State Farm to have small and insignificant correlations with brand preferences for other insurance companies. Consumers' brand preferences for Allstate show large positive correlations with those for AIG and Nationwide and a large negative correlation with those for American Family.

[15] The fit of the alternative model where I control for demographic and psychographic factors, and regional fixed effects in the search cost instead of the utility function is worse (−2975.74) than the fit of the model where these factors influence consumer utility (−2974.69), so I choose the latter model.

TABLE 9 **Model 2**

	Estimate	Standard Error		Estimate	Standard Error
Brand Preferences	μ_α		*Brand Preferences*	σ_α	
21st Century	−.1433	(.3191)	21st Century	.0403***	(.0034)
AIG	.4529	(.3057)	AIG	.2378***	(.0465)
Allstate	.2470	(.3205)	Allstate	.2902***	(.0586)
American Family	−.0886	(.4377)	American Family	.4728***	(.1086)
Erie	−.0338	(.3395)	Erie	.2398**	(.0892)
Farmers	−.1174	(.3197)	Farmers	.2348	(.1559)
Geico	−.3033	(.3218)	Geico	.4178***	(.0916)
GMAC	−.1876	(.3661)	GMAC	.3492***	(.1010)
The Hartford	.3199	(.3109)	The Hartford	.4531**	(.1462)
Liberty Mutual	.0810	(.3113)	Liberty Mutual	.6264*	(.3099)
Mercury	−.1365	(.3385)	Mercury	.8844***	(.2516)
MetLife	−.1408	(.3475)	MetLife	.4111***	(.1081)
Nationwide	−.1041	(.3313)	Nationwide	.6862***	(.1729)
Progressive	.2026	(.3142)	Progressive	.8298***	(.2081)
Safeco	−.6591	(.3280)	Safeco	.4656**	(.1465)
State Farm	.0112	(.3769)	State Farm	.6267	(1.1042)
Travelers	.1427	(.3276)	Travelers	.7588***	(.1838)
Other Parameters			*Switching Costs*		
Price	−.3969***	(.0321)	Constant	−1.7629***	(.3527)
Recall*advertising	.1441***	(.0470)	Age	.0029	(.0018)
			Gender	−.3134*	(.1304)
Obs. Brand Preferences			Income \$25,000–\$49,999	−.4656***	(.1032)
Proven reliability	.3900***	(.0356)	Income \$50,000–\$74,999	−.2274**	(.0688)
Out-of-the-Box character	.1389*	(.0585)	Income \$75,000–\$99,999	−.0345	(.0817)
			Income \$100,000–\$149,999	.5484***	(.1463)
Demographics			Income \$150,000 or more	.4291**	(.1661)
Excellent credit history	−1.7076**	(.6417)	High school graduate	−.0331	(.0271)
Good credit history	−1.6351*	(.6598)	College graduate	.1693**	(.0583)
Fair credit history	−.6776	(.9850)	Some graduate courses	.1554	(.1392)
Age	−.0005	(.0113)	Advanced degree	.5804***	(.0617)
Male	−.2095	(.3190)	Attitude towards auto		
Married	.1057	(.3647)	Insurance shopping &		
Divorced/Separated	.8745	(.5800)	switching	.2449*	(.1025)
Widowed	−.2789	(1.3950)	New technology adoption	.0671**	(.0240)
Domestic partnership	.3495	(.6900)	Technology usage	−.2287***	(.0348)
Medium city suburb	.0911	(.5268)	Loyalty	.0051	(.0471)
Large city suburb	−.6114	(.4867)	Interest in finance	−.3351***	(.0252)
Urban area	−.6789	(.5244)	Satisfaction with...		
			... Billings and payment process	.3587***	(.0719)
Psychographics			... Price	.3481***	(.0415)
Attitude towards auto			... Interacting with insurer	.1102***	(.0163)
Insurance shopping			... Policy offerings	−.2293	(.2042)
& switching	−.4294**	(.1555)	... Claims experience	.0669	(.0604)
New technology adoption	−.2280	(.1595)	Overall satisfaction	.4108***	(.0453)
Technology usage	−.1262	(.1680)			
Loyalty	−.0380	(.1629)	*Search Costs*		
Interest in finance	.2629	(.1785)	Constant	−.3951	(.2698)
			Mail	−.3787	(.8354)

(*Continued*)

The right side of Table 9 shows how customer inertia varies with observable characteristics. These observable characteristics can be divided into three groups. The first group consists of the intercept and demographic and psychographic factors that are uncorrelated with the observed measures of customer satisfaction, that is, gender, education, "Technology usage," "Loyalty," and "Interest in finance"; the second group consists of demographic and psychographic factors that are

TABLE 9 Continued

	Estimate	Standard Error		Estimate	Standard Error
Regions			Insurer website	-1.4796^{*}	(.6612)
Northeast	$-.6962$	(.5002)	Online quoting service	-1.6614^{**}	(.5883)
Mid-Atlantic	.1369	(.4739)	Insurer calling center	$-.5404$	(.4200)
Midwest	$-.0812$	(.4252)			
Florida	$-.0950$	(.5447)	*Fit Statistics*		
South	1.2844	(.9035)	Loglikelihood	-2974.69	
Texas	.1105	(.5221)	AIC	6401.38	
Mountain Area	$-.0875$	(.6881)	BIC	7497.75	

Notes: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.
Prices are measured in \$100. Advertising is measured in \$10,000,000.
$^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

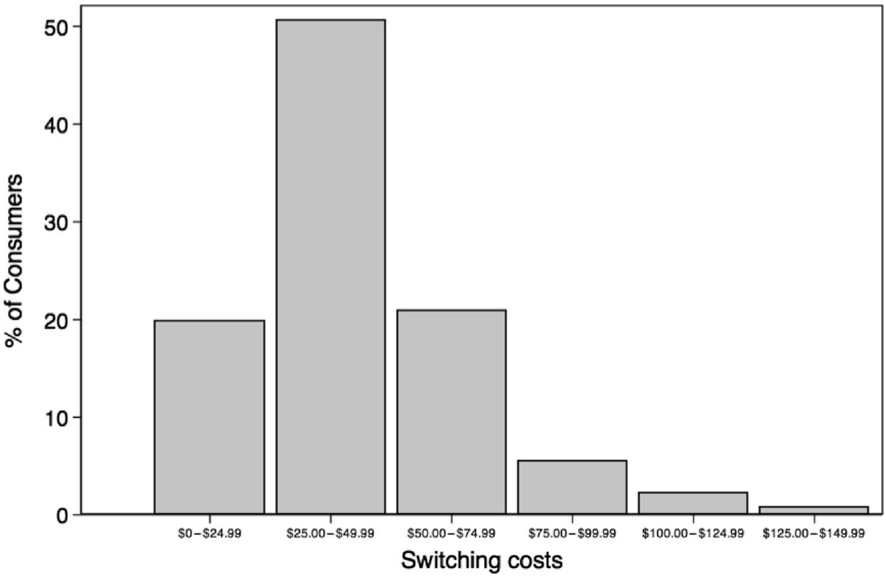
correlated with customer satisfaction, that is, age, income, and the remaining two psychographic factors; and the third group consists of the customer satisfaction measures. I attribute the part of customer inertia associated with the first group of variables to customer switching costs and the part of customer inertia associated with the third group of variables to satisfaction-based inertia or loyalty. The second group of variables, that is, those demographic and psychographic factors that are correlated with customer satisfaction measures, can be attributed to either customer switching costs or satisfaction based inertia. Here, I attribute it to customer switching costs and also report estimates under the alternative of attributing it to satisfaction-based inertia in footnote 16. I find no significant effects of age, but do find significantly higher switching costs for women when compared to men and switching costs to increase with income. Several psychographic factors also significantly influence switching costs. The more consumers dislike the auto insurance shopping and switching process, the higher their switching costs. Whereas “Technology usage” increases switching costs, “New technology adoption” and “Interest in finance” decreases them. “Interest in finance” captures a consumer’s interest in financial markets and publications. This factor is also likely to capture a consumer’s financial savviness, which decreases his switching costs, as he is more willing to switch to a new auto insurance provider if this is advantageous for him. Finally, I also look at how customer inertia varies with satisfaction in several areas. I find four effects to be significant: customer inertia increases with satisfaction with the billing and payment process, prices, interaction with insurer, and overall satisfaction. Satisfaction in other areas (policy offerings and claims service) has no significant effects.

The right side of Table 9 also shows how search costs vary with quoting channel. The search cost constant denotes the cost of collecting a quote through an agent. Search costs are 77% to 81% lower when consumers collect their quotes through online channels (insurer website, online quoting service) compared when they do so through agents. The cost of collecting a price quote by mail is 32% lower than through agents and the cost of collecting a price quote through an insurer calling center is 42% lower than through agents.

□ **Search and switching costs.** I now discuss search and switching costs in terms of dollars. I find search costs (per search) to be \$169.72 when searching through agents, \$116.21 when searching by mail, \$98.86 through calling centers, \$38.65 through insurer websites, and \$32.22 through online quoting services. Dahlby and West (1986) estimated search costs to be between \$131 and \$570 (adjusted for inflation and converted from Canadian dollars) for auto insurance in the seventies in Canada. My search cost estimates are lower. I attribute this to the data used by Dahlby and West (1986) having been collected partially in rural Canada, where the density of agents was lower, and to the introductions of calling centers and the Internet, which significantly lowered consumer search costs.

FIGURE 2

SWITCHING COST DISTRIBUTION



Average switching costs are $42.02, but there is much variation in switching costs based on observable characteristics as shown in Figure 2.[16] Cummins, McGill, Winklevoss, and Zelten (1983) found switching costs to equal 20% of the premium paid, which would be $118.59 with my data. Berger, Kleindorfer, and Kunreuther (1989) found switching costs to lie between $185 and $381 (adjusted for inflation and converted from Canadian dollars), so their switching cost estimate in today's dollars is considerably higher. My switching cost estimates are considerably smaller than those found by previous literature. I attribute this to the fact that previous literature was not able to differentiate between consumer inertia due to customer satisfaction and consumer inertia due to switching costs, and attributed all observed inertia to switching costs. If I follow this approach, I find the median value of consumer inertia to be $403.50, which is even higher than the estimates reported by Berger, Kleindorfer, and Kunreuther (1989).

My search and switching cost estimates underline the magnitude of market frictions in insurance markets and confirm Einav, Finkelstein, and Levin's (2010) expectation that market frictions are substantial in insurance markets due to the infrequency of purchases and due to price customization. Because of the sizable costs that consumers have to "pay" to learn about policy characteristics (e.g., price) and to switch providers, they decide to go through this process infrequently and leave a lot of money on the table. This also applies to other types of insurance products. Handel (2013) found the cost of inertia in health insurance for the average employee to be about $2000. These cost estimates underscore the importance of incorporating market frictions when estimating demand for insurance. Due to the high levels of search and switching costs, consumers make purchase decisions under limited information. Assuming full information will lead to biased preference estimates (e.g., Sovinsky, 2008; Koulayev, 2013; Pires, 2013) and misleading conclusions in welfare analyses (e.g., Handel, 2013).

□ **Price elasticities.** Table 10 shows the own-price elasticities implied by the model. The mean price elasticity across all companies is -1.08 and the company-specific own-price elasticities

[16] Under the alternative specification of attributing the correlated variables age, income, and the two psychographic factors to satisfaction-based inertia instead of switching costs, average switching costs are $43.00.

TABLE 10 Implied Own-Price Elasticities

	Estimates	Standard Errors
21st Century	−1.17	(.16)
AIG	−1.35	(.13)
Allstate	−1.01	(.15)
American Family	−.78	(.11)
Erie	−.76	(.18)
Farmers	−.98	(.15)
Geico	−.86	(.12)
GMAC	−1.58	(.20)
The Hartford	−.87	(.14)
Liberty Mutual	−1.20	(.22)
Mercury	−1.14	(.16)
MetLife	−1.35	(.11)
Nationwide	−1.08	(.13)
Progressive	−1.11	(.10)
Safeco	−1.62	(.15)
State Farm	−.75	(.17)
Travelers	−1.43	(.14)
Mean	−1.08	(.14)

vary from −.55 to −1.42. A strong contrast is found when the own-price elasticities calculated under limited information are compared to those estimated under full information. The average own-price elasticity under full information is 1.07. The positive sign of the price elasticity is counterintuitive and comes from the positive price coefficient when demand for auto insurance is estimated under full information. The reason for the positive price coefficient is the following: recall that there are 17 companies in the auto insurance market and that consumers, on average, consider 3 companies. When demand is estimated under the full information assumption, in many cases consumers do not pick the lowest or even one of the lowest priced options among the 17 companies. Under full information, this behavior is attributed to the consumer being insensitive to prices or, in this specific market, even preferring higher to lower prices (holding everything else such as coverage constant). Under limited information, the model can distinguish between the consumer not picking a low-priced option because he does not know about it (due to search costs) and the consumer being insensitive to prices. I conclude that accounting for market frictions is important in estimating price elasticities in insurance markets.

8. Counterfactuals

■ In this section, I present the results from two counterfactuals. It should be noted that the model is a partial equilibrium model. Thus any counterfactuals capture only consequences on the demand side, that is, I do not model premia adjustments on the supply side. The results can be interpreted as short-run market effects due to changes in the underlying structural parameters.

□ **Decomposition of customer retention.** In this counterfactual, I study how each of the three potential main sources—search costs, switching costs, and customer satisfaction—contribute to the high observed customer retention rate. Note that a part of the customer retention rate is also a consequence of consumer preferences other than those associated with inertia (e.g., brand intercepts, advertising, etc.). I refer to this retention rate as the baseline retention rate. The retention rate predicted by my model under current consumer behavior is 74.6%, whereas the baseline retention rate is 8.6%.

I first explore how the retention rate changes as each of the four potential sources is eliminated individually. When search costs are eliminated, the retention rate drops to 42.5%. When switching costs are eliminated, the retention rate decreases to 73.6% and when the effects of

TABLE 11 Consumer Welfare Counterfactual Results

	All Consumers	Switchers	Non-Switchers
Search Cost Elimination			
Percentage of all consumers		60.38%	39.62%
Change in consumer welfare per consumer	\$859.03	\$943.34	\$730.58
Change in consumer welfare as percentage of currently paid premium	158.06%	177.05%	129.12%
Average currently paid premium	\$592.97	\$589.85	\$601.47
average predicted premium change	−\$21.31	−\$35.30	\$0
Switching Cost Elimination			
Percentage of all consumers		30.62%	69.38%
Change in consumer welfare per consumer	\$50.27	\$48.72	\$50.95
Change in consumer welfare as percentage of currently paid premium	8.56%	8.01%	8.80%
Average currently paid premium	\$592.97	\$586.36	\$598.03
Average predicted premium change	−\$10.02	−\$31.65	\$0
Market Frictions Elimination			
Percentage of all consumers		61.90%	38.10%
Change in consumer welfare per consumer	\$881.78	\$969.23	\$739.71
Change in consumer welfare as percentage of currently paid premium	162.74%	182.28%	130.99%
Average currently paid premium	\$592.97	\$590.64	\$600.64
Average predicted premium change	−\$21.00	−\$33.93	\$0

customer satisfaction are eliminated, the retention rate drops to 59.9%. To put it differently, eliminating search costs reduces the retention rate by 43.0%, whereas removing customer satisfaction and switching costs decreases the retention rate by 19.3% and 1.4%, respectively.

When quantifying the effects of an elimination of multiple potential retention sources, it is important to note that the sources influence each other and, thus, the reduction in retention depends on the elimination sequence (e.g., first search costs, then switching costs, and last customer satisfaction). Although the specific amounts by which the retention rate decreases vary depending on the elimination sequence, the largest drop in the retention rate (in %) across all possible sequences comes from eliminating search costs followed by removing customer satisfaction, and, last, by eliminating switching costs. I conclude that removing search costs is the most powerful lever to decrease the retention rate in the US auto insurance industry. I further note that the baseline retention rate due to consumer preferences other than those associated with inertia is about 9%.

□ **Consumer welfare.** In the second counterfactual, I explore how much consumers would gain by living in a world without any market frictions, that is, without search or switching costs. To do so, I compare the resulting consumer welfare from the limited information model (Model 2) to the predicted consumer welfare using the preference estimates from Model 2 after eliminating the market frictions. As is well known, consumer welfare in discrete-choice models is only identified up to a constant (Small and Rosen, 1981), so I report the change in consumer welfare going from a world with market frictions to a world without. Table 11 shows all results.

When only search costs are eliminated, consumer welfare per person increases, on average, by \$859.03 or 158.06% of the currently paid premium. Although this increase is very large, recall that consumer welfare usually increases as new options are added to a consumer's choice set. Given that consumers, on average, consider three companies and there are 11 to 17 insurers operating in the states represented in my data, the elimination of search costs results in consumers' consideration sets increasing in size four to six times. When only switching costs are removed, consumer welfare per person increases, on average, by \$50.27, or 8.56%, of the currently paid premium—a result which is in line with the estimates found by previous literature (e.g., Handel, 2013). Thus, the increase in consumer welfare from an elimination of search costs is about 17 times larger than the increase from an elimination of switching costs. Finally, consumer welfare increases, on average, by $881.78 or 162.74%, of the currently paid premium when consumers live in a world without any market frictions.

Next, I evaluate how a removal of market frictions changes consumer behavior. First, I find that, on average, 60.38% of consumers change the insurance company they purchase a policy from after the elimination of search costs. If switching costs are eliminated, 30.62% of consumers switch their insurance provider. Finally, when both market frictions are eliminated, 61.90% of consumers switch insurance providers. These high switching rates have the potential to cause significant changes to the marketplace if market frictions are eliminated.[17] How does welfare change for consumers who switch compared to consumers who do not switch? When search costs (either alone or together with switching costs) are eliminated, the increase in consumer welfare, both in terms of dollars and percentage of currently paid premium, is larger for Switchers than for Non-Switchers. The situation is reversed when only switching costs are removed. In Table 11, I also report the average currently paid premia for Switchers and Non-Switchers to show that the different percentage of changes in currently paid premia are not primarily driven by different base amounts.

Finally, I investigate the change in premia consumers are paying when market frictions are eliminated. Overall, the average predicted premium decreases by $10 to $20 when one or both types of market frictions are eliminated. Interestingly, among the Switchers the decrease amounts to $30–$35 for all three scenarios. This decrease of about 5% compared to the currently paid premium is similar to the one found by Kling, Mullainathan, Shafir, Vermeulen, and Wrobel (2012) for Medicare Plan D in an experimental setting where they provided subjects with personalized price information. My results also provide evidence that the majority of the increase in consumer welfare due to an elimination of market frictions comes from the "option value" of more companies (when search costs are eliminated) and from consumers finding a company that better "fits" their preferences rather than from consumers unanimously switching to the lowest priced option.

9. Limitations and future research

■ There are several limitations to my research. First, the model describes the consumer search process and the purchase decision given a choice of a policy with certain characteristics (coverage choices, payment terms), that is, I do not jointly model policy choice and purchase. The model assumes that consumers first make the decision what policy to buy and then start the shopping process. It is left for future research to develop a model where consumers choose policy characteristics and search at the same time while evaluating different policies. Second, I assume that consumers have rational expectations about prices for all companies in the market. As a consequence, consumers are assumed to be aware of all the companies operating in their markets and to have rational expectations about prices. Clearly, a model that uses information on all three stages of the purchase process (awareness, consideration, choice) would provide further insights into the first two stages. By the same token, a model that has information on consumer price expectations or that is able to recover them would enable researchers to test the hypothesis of rational price expectations.

Third, an area that future research could focus on is disentangling the part of search cost that is due to time cost from the part that is due to psychological cost. The results would help researchers understand why search costs have not disappeared with the introduction of the Internet. Finally, I do not account for asymmetric information in the model, and therefore cannot compare the welfare loss due to market frictions to the welfare loss stemming from asymmetric information. It is left for future research to develop and estimate a model containing both. The results of this article indicate that more emphasis should be put on including search rather than switching costs as the former are bigger drivers of consumer welfare changes.

[17] The retention rate and consumer welfare counterfactuals do not describe the same scenario: In the retention rate counterfactual, I studied whether consumers would switch their insurance provider from time period $t-1$ to time period t. In this counterfactual, I investigate whether consumers would switch away from their current insurance provider.

10. Conclusion

■ In this article, I quantify search and switching costs in the US auto insurance industry. I find average switching costs of about $40, the cost of one price search over the Internet to be about $35, and the cost of a price search through local agents, mail, and calling centers to be $170, $115 and $100, respectively. These levels of search and switching costs provide an explanation for the high observed retention rate and the high savings advertised by insurance providers upon switching insurers in this industry. Zeroing in on customer retention, I show that search costs are the main driver of the high retention rate found in the US auto insurance industry when compared to switching costs and customer satisfaction. Further, I study the effects of eliminating market frictions on consumer welfare. Search costs are the main lever in increasing consumer welfare with the majority of the increase stemming from consumers' "option value" of being able to choose from a wider range of companies. The change in average predicted premium is moderate.

I contribute to the search literature by developing a new estimation approach which overcomes the curse of dimensionality found in simultaneous search models. I contribute to the insurance literature by providing further evidence of the magnitude and importance of market frictions in insurance markets. To summarize, market frictions play an important role in explaining the stickiness in consumer choices over time, and also significantly influence preference and price elasticity estimates as well as the results of consumer welfare analyses.

Appendix A

Appendix A contains a description of the original data and the competitive premia reconstruction process as well as detailed descriptive statistics for the final data. Appendix B is comprised of a step-by-step description of the new estimation approach for the simultaneous search model and robustness checks regarding the estimation of consumer price beliefs, assumptions on the data reconstruction process, the price distributions and consumers' knowledge of the price distributions.

□ **Original data.** The data come from an insurance shopping study conducted in 2006 and 2007 by a large marketing research company. I observe from which companies consumers got quotes, with which company they signed, as well as how much they paid for their insurance policy. This gives me information on the number and identity of companies searched and the switching decision. In addition, I observe a nearly complete customer profile containing information on demographics, psychographics, advertising recall, drivers, cars, location, past claims history, and other insurance products (see Table 1 in the article for a detailed listing).

Even though I observe the most important variables, I do not have complete information about the respondent and his insurance policy. Some of the variables that I do not observe in the original data are premia with the companies the consumer considered but did *not* purchase from, coverage choices, social security and VIN (vehicle identification) numbers, age of drivers other than the primary driver on the insurance policy, etc. Because prices are an important part of the utility function, I reconstructed the prices for all companies that were considered by consumers in the data. In the process of doing so, I also reconstructed each consumer's coverage choice. I discuss this premia reconstruction process in detail in the next section of this Appendix. I made assumptions about the unobserved variables that I do *not* reconstruct, e.g., social security and VIN numbers, age of the other drivers on the insurance policy, etc., and I discuss these assumptions in the next section as well.

To ensure the representativeness of my data set, vis-a-vis the population of consumers purchasing auto insurance, I use representativeness weights provided by the marketing research company to summarize my data and to make predictions. Representativeness weights are weights assigned to each consumer with the goal of creating a data set that is representative of the population with respect to demographics. These weights vary from .45 to 2.06. Results are robust to ignoring representative weights.

Competitive premia reconstruction. I observe from which companies each consumer got an insurance quote, but do not have information on the quoted premia other than from the company finally chosen. To be able to estimate the model, I needed to reconstruct these competitive quotes. Because the data are collected between April 1, 2006 and April 30, 2007, I needed to translate current quotes (that I can collect) into those that are likely to have prevailed at the time the consumer was seeking the quote. The quote reconstruction and time adjustment were done the following way:

(i) I collected all rate change filings for all insurance companies in all states between April 1, 2006 and December 2008. Rate change filings reflect the average percentage change in premium for customers as a consequence of a change in a company's pricing schedule.

TABLE A1 Data Assumptions for Price Reconstructions

1.	All quotes are collected without SSN or VIN.
2.	All parties in the household work full-time, children under age 18 go to school, children between age 18–22 go to college, children age 23 and older work full-time. Children who go to school or college qualify for the Good Student Discount.
3.	If there are two or more drivers on the policy: if the respondent is married or in a domestic partnership, the second driver is a spouse or partner. Male spouses/partners are three years older than female respondents, female spouses/partners are three years younger than male respondents. If the respondent is 40 years or older and the second driver is under 25 years old, I assume it is a daughter. The third and fourth drivers are assumed to be children. Their age is picked in accordance with the drivers under 25 years variable.
4.	All other characteristics for the second, third, and fourth driver are assumed to be similar to the respondent.
5.	If the respondent is over 60 years old, it is assumed that he/she is retired, uses the car for pleasure and drives 10,000 miles per year.
6.	As I assume that all drivers work full-time, I assume that they commute to work (five days a week) 10 miles. The annual mileage is 15000. If there are more cars than drivers on the policy, I assume that the additional cars are used for pleasure and driven 5000 miles annually.
7.	The respondent is the driver of the primary vehicle, the second driver is the primary driver of the second vehicle, etc. The second vehicle is a 2000 Honda Civic DX, the third car is a 1999 Ford Escort.
8.	All respondents got their driver's licenses at age 16. No driver's license suspensions or revocations, no major violations. All respondents have continuously had insurance while having a car.
9.	All vehicles are owned. The respondent is the original owner if the car is younger than five years.
10.	Same coverage levels are picked for all cars under the policy.
11.	All members of the household have health insurance.
12.	No existing damage on cars.
13.	Insurance policy premia are paid in full.
14.	To determine whether a respondent owns a home or not, the two variables "Homeowner insurance with current auto insurer" and "Homeowner insurance with other insurer" were used. If either was indicated to be the case, the respondent owns a home. If it was required to differentiate between owning a house and owning a condo, a condo was picked for people under 30 years and a house for people over 30 years. If no homeowner insurance was indicated, it was assumed that the respondent rents.
15.	If it is required to pick an occupation, one was chosen that matches education and income levels. Occupations that often qualify for special discounts at some insurance companies (e.g., nurse, physician, firefighter, police officer, teacher, etc.) were avoided.

(ii) I adjusted the premium the consumer paid with the chosen provider by the rate percentage change since purchase time. The underlying assumption behind this is that the consumer's premium would have changed in a manner similar to the average premium.

(iii) I inferred the consumer's policy coverage levels by requesting a new quote that matches the adjusted cited premium (within +/- $10).

(iv) Using the consumer profile and policy coverage levels, I requested the competitive quotes. I did so by going to the websites of all insurance companies that a consumer listed as having collected a quote from, completing the online quote request forms with the consumer's personal information and coverage choices, and recording the quoted premium. To get a clean picture, I constrain all respondents to be looking for auto insurance only, own three or fewer vehicles, and have four or fewer drivers insured under the policy.

To infer coverage levels in step (iii) and to request new quotes in step (iv), I need information such as age and gender of all drivers; year, make, model, and VIN of all cars; whether there is existing damage on the cars; how the insurance premium is paid (in full or monthly installments); etc. Although the data contain information on the age and gender of the primary driver, and year, make, and model of the primary car, I do not have information on age and gender of drivers other than the primary driver (but I know the number of drivers as well as the marital status of the primary driver), year, make, and model of other than the primary car (but I know the number of cars on the insurance policy), VIN for all the cars, whether there is existing damage on the cars, and how the insurance premium was paid. I made assumptions for these and other unobserved variables. The complete list of assumptions is shown in Table A1. As information on these variables that I do not observe is required to get a quote, I would not have been able to recover coverage choices and collect the missing premia without making them. I made assumptions for the unobserved variables in a way that they were consistent within a respondent and across insurance companies as well as across all respondents. This procedure ensures that I did not introduce any heterogeneity in consumer characteristics that did not actually exist in the original data. I assess the robustness of the results to these assumptions in the fourth subsection of Appendix B.

Consider consumer A who is male, 55 years old, married, lives in Illinois (urban area), has two cars and three drivers on his policy, one of whom is under 25 years old.[18] Consumer A has previously been insured with Safeco, received a renewal offer of $997.29, and requested two additional price quotes from MetLife and Travelers. The reconstructed premium quotes for MetLife and Travelers are $1203.84 and $1221.76, respectively. Consumer B is female, 54 years old, married, lives in California (rural area), has three cars and three drivers on her policy. She has previously been insured with Geico and received a renewal offer of $537.86. Additionally, she also requested a quote from 21st Century ($658.24), Farmers ($783.60), and Progressive ($832.48). Finally, consider consumer C who is male, 26 years old, single, lives in New Jersey (suburb of medium city), has one car and one driver on his policy and had two or more tickets (excl. parking tickets) in the past three years. Consumer C has previously been insured with Liberty Mutual and received a renewal offer of $1387.68. He also requested premium quotes from 21st Century ($1405.57) and AIG ($1171.31). For consumers A and B, their previous insurer offers the lowest premium; for consumer C, a newly searched company offers the lowest premium. The range of insurance premia, given a consumer's decision to collect two or three quotes in addition to the renewal offer from the previous insurer, is $224.47, $294.62, and $234.36, respectively. These premium range estimates show that, in the data reconstruction process, I was able to recover competitive quotes that are reasonable.

Original and final data. The original data set contained 2950 respondents from all US states except Massachusetts. I was able to get the rate change filings from 32 states. These states contain the biggest and most important auto insurance markets (California, Florida, Texas, Michigan, Pennsylvania, New Jersey, New York, Ohio, Illinois) and also over 70% of the respondents from the original data set. My final data set is considerably smaller for the following reasons:

(i) Recreating the competitive quotes involved recovering the respondent's policy's coverage levels. If the respondent was insured with an auto insurance company that required a social security number to get a quote (e.g., AAA) or being a member or a relative of a member of the US military (USAA), it was not possible to recover the coverage levels and reconstruct the competitive quotes. This is by far the most important reason for the shrinkage in data set size.

(ii) If the respondent was insured with a rather small insurance company which does not offer online quotes, or if the respondent was insured with an insurance company that does not offer online insurance quotes in this specific state (e.g., Nationwide does not offer online quotes in California or Florida, but does so in many other states), it was not possible to recover coverage levels and reconstruct competitive quotes.

(iii) Only respondents for whom I was able to recover the coverage levels and all competitive quotes are included in the final data set.

(iv) Thirty seven respondents who were outliers were excluded based on their characteristics (e.g., 95 years old) or reported prices that were not credible (e.g., $200 for a six-months policy with State Farm in Florida with four drivers and three cars).

The final data set has 945 respondents. Even though I am only able to use about one third of the original data set because of the aforementioned reasons, the final data are very similar to the original data in almost all characteristics. Table A2 shows descriptive statistics for the original and final data. The main difference between my original and final data is the slightly higher average number of quotes in the original data, that is, 3.34 in the original versus 2.96 in the final data set; the two data sets are very similar in all other aspects. The smaller average number of quotes is likely due to the data reconstruction, as it is easier to reconstruct all competitive prices for a smaller rather than a larger number of quotes.

Data description. Table 2 (in the article) contains descriptive statistics for the final data set. Consumers get on average 2.96 quotes (including one from their previous insurer) and collect information on auto insurance from 2.12 sources. Figure 1 (in the article) shows the distribution of consideration set sizes. The majority of consumers collect two or three quotes. They use two different methods to collect quotes (e.g., insurer website, agent, etc.) and need about 1.5 weeks each to gather price quotes and then decide on their insurance provider. Consumers have been with their auto insurance provider, on average, for seven years, and have 1.64 drivers on the policy who drive 1.58 cars. The average premium with a consumer's previous insurer was $764.41, whereas it is $554.49 for the same group of consumers with the current insurer.[19] Across all consumers in the data, the average premium with the current insurer is $592.97. Comparing the mean characteristics for each respondent type (No search/No switch, Search/No switch, Search/Switch), I find consumers who neither search nor switch obviously get only one quote—the one that their previous insurer sends to them; consumers who search, but decide not to switch, collect 2.89 quotes, and consumers who search and switch gather 3.51 quotes. Although there is not much difference in the number of information sources and online quoting sites visited across the three respondent types, consumers who search use more methods to obtain quotes. Consumers who neither search nor switch pay the highest average premium ($660.13), followed by consumers who search, but decide to stay with their previous insurer ($606.36). Consumers who search and switch pay on average $551.44.

The lower part of Table 2 provides a description of measures of customer satisfaction with the previous auto insurance provider, which were collected in five areas: billings and payment process, price, interaction with insurer, policy offerings, claims experience, and overall experience. All variables were measured on a scale from 1 to 10 where 1 indicates

[18] Consumer A, and in the following, Consumers B and C are consumers from my data.

[19] Some consumers did not provide the premium they paid with their previous insurer.

TABLE A2 Original and Final Data Statistics Comparison

	Final Data	Original Data
Proportion of Consumers in Percent		
Female	36.32	34.73
Period with no auto insurance during last three years	3.03	2.78
Relocated during the past 12 months	19.46	20.72
Presence of children	25.79	26.66
Driver under 25 years	8.25	10.74
Excellent credit history	65.30	63.82
Good credit history	22.83	23.57
Fair credit history	8.46	7.99
Poor credit history	1.89	2.81
Married	56.07	57.82
Divorced/Separated	13.23	12.33
Widowed	.87	1.74
Single	22.48	21.44
Domestic partnership	6.19	5.52
Income below \$50,000	20.71	19.91
Income \$50,000–\$99,999	39.84	40.89
Income \$100,000–\$149,999	24.65	18.76
Income \$150,000 or more	14.80	8.75
High school graduate or less	7.24	5.58
Some college or college graduate	54.72	56.70
Some graduate courses or advanced degree	38.04	37.17
Rural area	14.67	14.99
Medium city suburb	29.63	31.24
Large city suburb	34.38	33.47
Urban area	19.66	19.13
Average Values		
Number of quotes	2.96	3.34
Number of information sources	2.12	2.20
Number of methods to obtain a quote	2.01	2.09
Length of price gathering process	1.54	1.65
Length of choosing process	1.36	1.52
Number of vehicles	1.58	1.62
Number of drivers	1.64	1.69
Vehicle year	2001.98	2001.88
Premium with current insurer	592.97	612.60
Number of hours online	15.21	15.29
Age	45.23	45.09
Number of people in the household	2.33	2.39

"unacceptable," 5 indicates "average," and 10 indicates "outstanding." Auto insurance customers are, on average, most satisfied with the interactions with their insurance companies and their overall experience (8.24 and 8.33, respectively) and least satisfied with the policy offerings and price (7.93 and 7.95, respectively). There is noticeable variation in customer satisfaction across consumers as the standard deviations of the customer satisfaction measures range from 1.51 to 1.90 on a 10-point scale.

Table A3 shows descriptive statistics for the psychographic questions. The questions cover the areas of shopping habits, technology, personal finance, and auto insurance and are measured on a scale from 1 to 5 where 1 indicates "completely disagree" 3 indicates "neither disagree nor agree," and 5 indicates "completely agree." The standard deviations ranging from .76 to 1.18 on a 5-point scale indicate considerable variation in psychographics across consumers. Using factor analysis, I recovered five underlying factors, namely, "Attitude toward Auto Insurance Shopping & Switching," "New Technology Adoption," "Technology Usage," "Loyalty," and "Interest in Finance."

Table A4 shows descriptive statistics for consumer attitudes toward each considered insurance company. The questions cover areas of proven reliability and out-of-the-box character of an insurance company and are measured on a scale from 1 to 7. The standard deviations ranging from 1.27 to 1.41 on a 7-point scale indicate considerable variation in attitudes across consumers. Using factor analysis, I recovered two underlying factors, namely, "Proven Reliability" and "Out-of-the-Box Character."

TABLE A3 Descriptive Statistics for Psychographic Questions

Please indicate your agreement with each of the following statements regarding...	Mean	Standard Deviation	Factor
... your shopping habits.			
I am always one of the first of my friends to try new products or services.	2.77	.96	B
... your brand loyalty and technology.			
If a product or service is offered by a company I trust, I will buy it even if it is slightly more expensive.	3.43	.85	D
Compared to other people, I am more likely to be loyal to a brand.	3.17	.86	D
When I find a brand I like, I stick with it.	3.62	.78	D
Computers are too confusing to be of much use to me.	1.46	.76	C
I enjoy reading about new technology products.	3.39	.97	B
I am among the first of my friends and colleagues to try new technology products.	2.91	1.03	B
Technology has little impact on my daily life.	1.88	.89	C
... your personal finances.			
I find the ups and downs of the financial markets exciting.	2.64	.98	E
I regularly read financial news or financial publications.	3.12	1.18	E
... auto insurance.			
Switching to another auto insurer is not worth the risk.	2.35	.91	A
Shopping for a new auto insurer is too difficult or time consuming.	2.39	.93	A
I have invested too much time into building a relationship with my current agent or insurer to switch to a new auto insurer.	2.31	.98	A

Notes: A: Attitude toward Auto Insurance Shopping & Switching; B: New Technology Adoption; C: Technology Usage; D: Loyalty; E: Interest in Finance.

TABLE A4 Descriptive Statistics for Attitudinal Questions Toward Auto Insurance Companies

Please take a look at the pairs of statements below and select the box closest to the statement that you think best describes the auto insurer.	Mean	Standard Deviation	Factor
Conventional (1) vs. Innovative (7)	4.18	1.41	B
Unproven (1) vs. Trusted (7)	5.16	1.37	A
Slow (1) vs. Responsive (7)	4.94	1.40	A
Careless (1) vs. Protective (7)	4.90	1.27	A
Volatile (1) vs. Stable (7)	5.15	1.32	A
Serious (1) vs. Fun (7)	3.87	1.35	B

Notes: A: Proven Reliability; B: Out-of-the-Box Character.

Table A5 contains information about the composition of consideration sets. The left column shows that more than half of the respondents request a quote from Geico, followed by Progressive, Allstate, and State Farm. The right column accounts for limited availability, that is, the fact that not all auto insurance companies operate in all states. It shows the probability that a respondent considers an insurer if this insurer is offering policies in the respondent's state. The largest differences are seen for American Family, Erie, and Mercury. These are companies which operate only in a few states, but have a relatively strong presence in these states.

Table 4 in the article shows the market shares, retention, and conversion rates, that is, given that a company is being considered, the probability that it will be chosen. Geico, Allstate, Progressive, and State Farm have the largest market shares with about 12% to 19%. Safeco and GMAC have the smallest market shares. The average retention rate is 74%. Allstate and State Farm have higher retention rates than Geico and Progressive (70% and 72% versus 64% and 63%). The companies with the highest conversion rates are, surprisingly, Erie and Travelers. Among the companies with the lowest conversion rates are not only the companies with the lowest market shares, Safeco and GMAC, but also two companies which have the highest and third-highest market shares, namely, Geico and Progressive. It seems that these

TABLE A5 Consideration Set Composition

Company	Considered by % Respondents	Accounting for Limited Availability[a]
21st Century	7.91	7.91
AIG	20.81	20.81
Allstate	36.60	36.60
American Family	6.61	23.22
Erie	5.00	11.77
Farmers	11.86	11.86
Geico	53.91	53.91
GMAC	5.65	5.68
The Hartford	13.98	13.98
Liberty Mutual	10.38	10.38
Mercury	5.23	7.68
MetLife	6.37	2.20
Nationwide	11.94	12.21
Progressive	46.98	46.98
Safeco	4.82	4.87
State Farm	34.26	34.26
Travelers	7.85	7.93

Notes: [a]Probability that respondent considers an insurer if this insurer is offering policies in the respondent's state.

TABLE A6 Average Monthly Advertising Spending in $1,000,000 and Advertising Recall

Company	Advertising Spending	Percentage of Respondents Recalling Advertising
21st Century	2.66	15.22
AIG	4.08	49.00
Allstate	27.03	78.66
American Family	2.53	20.16
Erie	.01	3.45
Farmers	4.72	36.05
Geico	45.89	90.13
GMAC	.02	20.66
The Hartford	.73	34.14
Liberty Mutual	5.72	38.11
Mercury	4.20	14.34
MetLife	.68	44.36
Nationwide	6.25	55.53
Progressive	29.56	78.62
Safeco	.03	13.41
State Farm	18.95	79.33
Travelers	.00	27.48

two companies are good at getting people to request quotes from them, but not good at converting these quotes into actual purchases.

There is one more piece of data from the shopping survey that I use in the model. Study participants were asked whether they recalled having seen advertising from a specific company during the last 12 months. The right column in Table A6 shows advertising recall by company. Geico has the highest recall rate with about 90%, followed by Allstate, Progressive, and State Farm with nearly 80%. Companies with some of the smallest market shares in the data—Erie, Safeco, and Mercury—also have the lowest recall rates.

Additional data. I also have data on radio and TV advertising spending by company and month in 2006 (see middle column, Table A6). Radio and TV advertising represents over 90% of insurance companies' total advertising budget. Geico spent the most with an average of nearly $46 million per month, followed by Allstate and Progressive, which spent an average of $27 million and $29.5 million, respectively, and State Farm, which spent an average of $19 million. Generally, there is considerable variation in advertising spending as some companies barely advertise or do not do so at all (e.g., Erie, GMAC, Safeco, Travelers).

Appendix B

□ **Estimation of consideration set and conditional purchase probabilities.** I use simulated maximum likelihood (SMLE) to estimate the model. The probability that a consumer picks consideration set Υ is given by

$$P_{i\Upsilon|\alpha,\epsilon} = \Pr\left(\min_{j\in S_i}\left(E\left[u_{ij}\right]\right) \geq \max_{j'\notin S_i}\left(E\left[u_{ij'}\right]\right) \quad \cap \quad \Gamma_{i,k+1} \geq \Gamma_{i,k'+1} \;\; \forall k \neq k'\right), \tag{B1}$$

and a consumer's conditional purchase probability is given by

$$P_{ij|\Upsilon,\alpha,\epsilon} = \left(u_{ij} \geq u_{ij'} \quad \forall j \neq j', \quad j, j' \in C_i\right). \tag{B2}$$

Both probabilities do not have a closed-form solution and both are nonsmooth. Because common optimization routines require smoothness, the nonsmooth probabilities would either require using non-gradient based optimization methods or taking a very large number of draws (simple frequency simulator, McFadden, 1989). Instead, I choose to smooth the probabilities using a scaled multivariate logistic CDF (Gumbel, 1961):

$$F\left(w_1, \ldots, w_T; s_1, \ldots, s_T\right) = \frac{1}{1 + \sum_{t=1}^{T} \exp\left(-s_t w_t\right)} \qquad \forall\, t = 1, \ldots, T, \tag{B3}$$

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

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

1. Take $q = 1, \ldots, Q$ draws from α_{ij} and ϵ_{ij} (for each consumer/company combination)
2. For each α_{ij} and ϵ_{ij} draw, calculate w_{qt} for the
   (a) Consideration set probabilities:
      i. Consumers who searched at least once (i.e., previous insurer + 1)
      $w^q_{1|\alpha,\epsilon} = \min_{j\in S_i}\left(E\left[u_{ij}\right]\right) - \max_{j'\notin S_i}\left(E\left[u_{ij'}\right]\right)$
      $w^q_{2|\alpha,\epsilon} = \Gamma_{i,k+1} - \max\left(\Gamma_{i,k'+1}\right)$
      ii. Consumers who did not search (i.e., previous insurer only)
      $w^q_{1|\alpha,\epsilon} = \Gamma_{i,1} - \max\left(\Gamma_{i,k'+1}\right) \quad \forall k' \neq 0$
   (b) Conditional purchase probabilities:
      $w^q_{1|\alpha,\epsilon} = u_{ij} - \max(u_{i,j'}) \qquad \forall j \neq j',\ \forall j, j' \in C_i$
3. Calculate the smoothed consideration set and conditional purchase probabilities using the scaled logistic CDF (Gumbel, 1961):
   (a) Consideration set probabilities:
      i. Consumers who searched at least once (i.e., previous insurer + 1)
      $P^q_{i\Upsilon|\alpha,\epsilon} = \frac{1}{1+\exp\left(-s_1 w^q_{1|\alpha,\epsilon}\right)+\exp\left(-s_2 w^q_{2|\alpha,\epsilon}\right)}$
      ii. Consumers who did not search (i.e., previous insurer only)
      $P^q_{i\Upsilon|\alpha,\epsilon} = \frac{1}{1+\exp\left(-s_1 w^q_{1|\alpha,\epsilon}\right)}$
   (b) Conditional purchase probabilities:
      $P^q_{ij|\Upsilon,\alpha,\epsilon} = \frac{1}{1+\exp\left(-s_1 w^q_{1|\alpha,\epsilon}\right)}$
4. Calculate the unconditional purchase probabilities by multiplying the consideration set and conditional purchase probabilities (see equation (11) in the article) and averaging them across all Q draws, i.e., $P_{ij} = \frac{1}{Q}\sum_{q=1}^{Q} P^q_{i\Upsilon|\alpha,\epsilon} P^q_{ij|\Upsilon,\alpha,\epsilon}$.

In the estimation, I use a scaling factor of $s_1 = s_2 = 15$ and take $Q = 50$ draws from the error distribution.

I test the performance of my estimation approach by simulating data on search set and purchase decisions for 1000 consumers. Consumers can choose among six brands with the first search being free. Similarly to Model 0 (from the article), consumers receive utility from a brand intercept, advertising, price, and an EV Type I distributed error term. I take 50 draws from the distribution of the error term and replicate the simulation 50 times. The true parameters and the estimation results are shown in Table 5 (in the article). The true parameter values are recovered well; they all lie within one standard error of the true values. I conclude that my estimation approach is able to recover the true parameter values.

Estimation of consumer price beliefs. In the model, I estimate consumer price beliefs using prices charged by previous insurers. A concern with this approach is selection. The ideal way to check for selection would be to collect quotes for all consumers and all companies.[20] Because this is impossible without unlimited resources,[21] I present two alternative robustness checks instead. In the first one, I estimate the same pricing regression using prices from all quoted companies (instead of previous insurer prices only) and compare the estimates and residual distributions. In the second robustness check, I collected quotes for all companies operating in a state for 30 consumers and estimated the pricing regression using these data.

[20] This means I would have to collect about 11000 quotes more.

[21] It took me about 6 months to collect 3000 quotes.

TABLE B1 Consumer Price Belief Estimations Using Previous Insurer and All Quoted Prices

	Previous Insurer Prices		All Quoted Prices	
	Estimate	Standard Error	Estimate	Standard Error
Location Parameter				
Constant	4.6501***	(.6695)	4.5733***	(.5784)
Male	−.1633	(.1322)	−.1673	(.1301)
Married	.1069	(.2573)	.0821	(.2357)
Divorced/Separated	−.0345	(.2373)	−.1977	(.2322)
Widowed	1.2789*	(.5829)	1.0604#	(.6138)
Domestic partnership	.3531	(.2985)	.3740	(.2939)
Age	−.0041	(.0057)	−.0080	(.0055)
Driver under age 25	.8572**	(.3043)	1.0463***	(.2760)
Two vehicles	1.6260***	(.1613)	1.4708***	(.1596)
Three vehicles	2.4145***	(.2745)	2.3960***	(.2590)
Two drivers	−.0889	(.2191)	−.0279	(.2103)
Three drivers	1.0885**	(.3909)	1.0090**	(.3839)
Four drivers	1.3607	(.8741)	1.3869	(.9326)
Medium city suburb	−.0839	(.2088)	−.1959	(.2027)
Large city suburb	.4570*	(.2091)	.4385*	(.2039)
Urban area	.4576#	(.2350)	.4900*	(.2247)
Home owner insurance with CI	−.1831	(.1479)	−.1884	(.1466)
Other insurance with CI	−.2938*	(.1466)	−.2703#	(.1437)
Two or more accidents	1.7930***	(.4757)	1.4992***	(.4567)
Two or more tickets	.9021***	(.3256)	1.2212***	(.3038)
Model age	−.0758***	(.0175)	−.0580***	(.0164)
21st Century	−.7351#	(.3945)	−.6035	(.3949)
AIG	−.3323	(.3510)	−.0125	(.3444)
Allstate	.0323	(.2986)	.0324	(.3007)
American Family	−1.4593***	(.4086)	−1.5976***	(.4064)
Erie	−1.5574***	(.4233)	−1.3369**	(.4165)
Farmers	−.8074*	(.3438)	−.8367*	(.3465)
Geico	−1.1550***	(.2894)	−1.0472***	(.2858)
GMAC	.2993	(.4532)	.6388	(.4542)
The Hartford	−1.0299**	(.3578)	−.7197*	(.3485)
Liberty Mutual	.0113	(.3257)	.2719	(.3242)
Mercury	−.2724	(.4279)	−.1330	(.4273)
MetLife	−.1436	(.4346)	.2400	(.4109)
Nationwide	−.3807	(.3354)	−.4085	(.3384)
Progressive	−.5688#	(.3105)	−.3802	(.3041)
Safeco	−.6217	(.5266)	.0247	(.4767)
Travelers	.2388	(.3712)	.1486	(.3757)
Chosen coverage	yes		yes	
State	yes		yes	
Make*class	yes		yes	
Scale Parameter				
Constant	1.4517***	(.0774)	1.4596***	(.0576)
Fit Statistic				
Loglikelihood	−1804.70		−1814.64	

Notes: Prices are measured in $100. CI: Current Insurer.
*** $p < .001$, ** $p < .01$, * $p < .05$, # $p < .10$.

Table B1 shows the estimates from the pricing regression using previous insurer prices on the left side and from the pricing regression using all quoted prices on the right side. Note that most coefficients have expected signs and reasonable magnitudes. For example, insuring a second vehicle costs about $130[22] for a six-months policy and having two or more accidents makes an insurance policy about $200[23] more expensive. The coefficient estimates across these two pricing

[22] $134.34 based on the previous insurer prices and $128.04 based on all quoted prices.
[23] $190.80 based on the previous insurer prices and $196.69 based on all quoted prices.

TABLE B2 Pricing Regressions

	Previous Insurer Prices		All Quoted Prices	
Variable	Estimate	Standard Error	Estimate	Standard Error
Intercept	1.9773*	(.7424)	2.4690***	(.5830)
Male	−.1664	(.1668)	−.2064	(.1316)
Married	−.9297**	(.2785)	−1.0845***	(.2273)
Divorced/Separated	−.1970	(.2690)	−.4406*	(.2182)
Widowed	.2683	(.7729)	−.0982	(.6670)
Domestic partnership	−.0809	(.3417)	−.5018#	(.2719)
Age	−.0189*	(.0065)	−.0286***	(.0052)
Driver under age 25	1.017*	(.4339)	.5822#	(.3429)
Male driver under age 25	.6802	(.5433)	1.1676*	(.4232)
Two vehicles	2.0510***	(.2004)	2.3324***	(.1617)
Three vehicles	4.1209***	(.3050)	4.6517***	(.2434)
Two drivers	.3482	(.2749)	.4501*	(.2224)
Three drivers	2.0190***	(.5067)	2.7491***	(.3916)
Four drivers	2.5340*	(.9241)	3.3351*	(1.3224)
Medium city suburb	−.0498	(.2565)	−.1441	(.1988)
Large city suburb	.6078*	(.2550)	.4633*	(.1971)
Urban area	.8257*	(.2827)	1.0085***	(.2243)
Home owner insurance with CI	−.0709	(.1631)	−.1450	(.1300)
Other insurance with CI	−.1989	(.1713)	−.5212***	(.1347)
Two or more accidents	2.5943***	(.4766)	3.4573***	(.3630)
Two or more tickets	1.4285***	(.3753)	1.9747***	(.2969)
Model age	−.0560*	(.0185)	−.0642***	(.0156)
Chosen coverage	yes		yes	
State	yes		yes	
Make*class	yes		yes	
R^2	.69		.57	

Notes: Prices are measured in \$100. CI: Current Insurer.
$^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$, $^{\#}p < .10$.

regressions are also quite similar in magnitude and lie within two standard errors of each other, suggesting some internal consistency. For example, the results from the previous insurer price distribution suggest that having home insurance with your auto insurance provider saves \$26.15 on the auto insurance premium, whereas the results from the all quotes pricing regression suggest that having homeowner insurance with your auto insurance provider saves \$21.58.

In the second robustness check, I collected quotes for all companies operating in a state for 30 consumers and estimated the pricing regression using these data. Because of the limited amount of data on premia from 30 consumers, I am not able to compare all coefficient estimates, but look at the key regression coefficients (e.g., marital status, number of vehicles, number of drivers, etc.) and find them to be similar to those from the all quoted prices regression. I conclude that selection does not appear to be a concern in these data.

Robustness regarding consumer price beliefs. In the article, I estimate consumer price beliefs by regressing all prices charged by previous insurers (pooled across consumers) on personal and policy characteristics as well as company-specific fixed effects. I use prices charged by previous insurers to reflect the consumer's knowledge of the prices present in the market before the search. An alternative assumption on the consumer's knowledge about prices is that they not only know about the price charged by previous insurers, but about all quoted prices. I examine the robustness of my model estimation results to this alternative consumer price belief estimation. The predicted prices I use in this estimation are based on the results from the two right columns in Table B1. The model estimation results are shown as Model R1 in Table B4. This model is the equivalent of Model 1 in the article, but for space reasons I report only the mean brand preferences in Table B4. The results are very similar to those for Model 1 using previous insurer prices for the consumer belief estimation (Table B1). Search costs and the value of consumer inertia in dollars are \$36.81 (per search) and \$463.02, respectively, compared to \$36.08 and \$475.30, respectively, for price beliefs based on previous insurer prices. The estimates show that my results are robust to the alternative assumption on how consumers form their price beliefs.

Assumptions during data reconstruction process. During the process of recontructing the competitive price quotes, I needed to make data assumptions (Table A1) to be able to recover the premia. A valid question is how these assumptions influence the results. Whereas it is prohibitively expensive to check the consequences of the assumptions on the price recovery process by reconstructing competitive prices using a different set of assumptions, I try to mitigate those concerns

TABLE B3 Company-Specific Price Residual Distributions

	Previous Insurer Prices		All Quoted Prices	
	Mean	Standard Deviation	Mean	Standard Deviation
21st Century	.0160	(1.9969)	−.0279	(2.1099)
AIG	.4048	(1.7310)	.9242	(2.9406)
Allstate	.2052	(1.6698)	.5836	(2.5510)
American Family	−.3630	(1.7035)	−.3239	(2.0323)
Erie	−.9257	(1.8152)	−1.1422	(2.0747)
Farmers	−.2356	(1.8103)	.0225	(2.9853)
Geico	−.5739	(1.4828)	−1.2113	(1.7951)
GMAC	.4843	(1.6781)	2.1580	(4.2409)
The Hartford	−.3975	(1.5367)	−.1195	(1.9534)
Liberty Mutual	.2463	(1.8025)	.1078	(2.3777)
Mercury	.2392	(1.7104)	−.2268	(1.7387)
MetLife	.9574	(1.7294)	.7586	(2.0137)
Nationwide	−.3813	(1.7538)	−.3315	(2.4103)
Progressive	.1368	(1.7007)	−.1018	(2.3157)
Safeco	.4037	(1.0683)	−.2736	(1.5583)
State Farm	.2623	(1.2756)	.2021	(1.9702)
Travelers	.7147	(1.6893)	.1729	(1.7164)

by estimating the model using consumers who purchased auto insurance for one driver and one car only and did not have home insurance. The reasoning behind using this subset of consumers for the robustness check is that assumptions on additional drivers and cars as well as details on other insurance products should have the strongest influence on premia. By focusing on the subset of consumers who purchased auto insurance for one driver and one car only and did not have home insurance, I avoid the effects of those assumptions on the estimates. The results are shown as Model R2 in Table B4. Note that for this robustness check I estimate the model without unobserved heterogeneity in the brand intercepts, as including unobserved heterogeneity is computationally not possible due to the smaller sample size. The estimates are similar to those for Model 0 for the whole data set (see Table 8). The largest differences can be found in the search cost estimate. Consumers seem to have smaller cost of search in utils and dollars. Search costs and the value of consumer inertia in dollars for this subset of consumers are \$35.20 (per search) and \$351.78, respectively, compared to \$41.81 and \$336.22, respectively, for the whole data set. I believe that the smaller search costs are due to the subsample consisting of younger, mostly single people or couples without children who make less money. Despite the small differences in estimates, my results are robust to the data reconstruction assumptions.

Hedonic price regressions and residual price distributions. When estimating the parameters of the EV Type I distribution for prices, the large scale parameter estimate points toward a substantial proportion of the variation in prices that remains unexplained. A different approach to evaluating the unexplained portion of variation in prices is running a hedonic price regression and looking at the R^2. Table B2 shows the results from two pricing regressions using prices charged by previous insurers and all quoted prices. The two middle columns show the estimates for the Previous Insurer Prices regression, the two columns at the right the estimates for All Quoted Prices regression. Note that all coefficients have the expected signs and reasonable magnitudes. The coefficient estimates across these two pricing regressions are also quite similar in magnitude and lie within two standard errors of each other, suggesting some internal consistency. The R^2 for the Previous Insurer and All Quoted Prices Regressions are .69 and .57, respectively, and support the view that I have information on most of the consumer characteristics that determine insurance premia. To show that these "low" R^2 are due to the fact that I combine prices across companies, I run company-specific pricing regressions. Due to data limitations, I am only able to do so for the four largest auto insurance companies (Allstate, Geico, Progressive, and State Farm). The R^2 of these separate pricing regressions (using all quoted prices) are .82, .80, .83, and .87, respectively. These regressions show that although the characteristics explain a substantial portion of variation in prices, there are nevertheless factors left out that can justify the assumption of price search as noted previously.

Table B3 describes the means and variances of the company-specific residual distributions for the Previous Insurer Prices regression on the left and for the All Quoted Prices regression on the right side that can be used to compare prices across consumers. For both pricing regressions, the company-specific residual means are directionally the same in most cases and, if the companies were ranked according to their residual means, companies which belong to the group with high residual means in the Previous Insurer Prices regression would remain in that group based on the results from the All Quoted Prices regression even if their exact rank might change slightly. The same applies to the companies with medium and low residual means. Further note that the standard deviations are substantial. This implies that there remain factors

TABLE B4 Robustness Checks

	R1		R2		R3		R4	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Brand Preferences		μ_α				μ_α		μ_α
21st Century	−2.3939***	(.2481)	−2.5209***	(.3623)	−2.2324***	(.3572)	−2.2247***	(.3240)
AIG	−1.8622***	(.2174)	−2.2958***	(.4275)	−1.6449***	(.3611)	−1.6069***	(.3451)
Allstate	−2.0368***	(.1964)	−2.3946***	(.5093)	−1.8248***	(.2982)	−1.7477***	(.3005)
American Family	−1.9277***	(.2738)	−2.1783***	(.4732)	−1.7154***	(.3507)	−1.7312***	(.3514)
Erie	−2.0549***	(.2691)	−3.1868***	(.4983)	−1.8652***	(.3612)	−1.8921***	(.3218)
Farmers	−2.1904***	(.2422)	−2.9087***	(.3471)	−2.0516***	(.3109)	−2.0156***	(.3040)
Geico	−2.8217***	(.1899)	−3.1086**	(.9734)	−2.6053***	(.2550)	−2.5426***	(.2847)
GMAC	−2.5576***	(.3284)	−3.1591**	(1.1899)	−2.1627***	(.3636)	−2.1277***	(.3690)
The Hartford	−1.9542***	(.2910)	−2.6766***	(.4113)	−1.7475***	(.3502)	−1.6981***	(.3403)
Liberty Mutual	−1.9371***	(.2651)	−2.3504***	(.3782)	−1.7248***	(.3139)	−1.6556***	(.3067)
Mercury	−2.5260***	(.2483)	−3.0688***	(.8287)	−2.3426***	(.3361)	−2.3018***	(.3398)
MetLife	−2.4362***	(.2547)	−3.1134***	(.4405)	−2.2333***	(.3408)	−2.1673***	(.3513)
Nationwide	−2.2972***	(.2849)	−3.4217**	(1.3122)	−2.0041***	(.2945)	−1.9731***	(.3212)
Progressive	−2.2209***	(.2130)	−2.3394***	(.5770)	−2.0205***	(.2853)	−1.9852***	(.3075)
Safeco	−2.9442***	(.3449)	−3.4202***	(.6068)	−2.7610***	(.4392)	−2.6937***	(.4436)
State Farm	−2.2372***	(.2253)	−2.6258***	(.4470)	−1.9665***	(.3594)	−1.9207***	(.3601)
Travelers	−2.2108***	(.3105)	−2.3765***	(.3978)	−1.9675***	(.3601)	−1.9416***	(.3426)
Other Parameters								
Price	−.3537***	(.0215)	−.3815***	(.0235)	−.3589***	(.0372)	−.3751***	(.0347)
Recall*advertising	.1291***	(.0465)	.1348	(.1755)	.1311***	(.0497)	.1235***	(.0502)
Inertia	.4933***	(.0378)	.2942**	(.1088)	.4950***	(.0524)	.4962***	(.0682)
Search cost	−2.0388***	(.3922)	−2.0005**	(.6172)	−1.2445***	(.3415)	−.7625**	(.2849)
Loglikelihood	−3,207.90		−2,174.50		−3,306.43		−3,303.00	
AIC	6,763.79		4,390.99		6,960.86		6,954.00	
BIC	7,607.90		4,507.86		7,804.97		7,798.11	

Notes: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Prices are measured in \$100. Advertising is measured in \$10,000,000.
***$p < .001$, **$p < .01$.

that I do not observe that might cause actual prices, to be different from expected prices and consumers have to search to learn the actual premium an insurance company will charge them.

Consumer's knowledge of the price distributions. One of the assumptions of the model is that consumers know the distributions of prices present in the market with the parameters of these distributions coming from the observed price distributions in the data. To examine the sensitivity of the results to this assumption, in particular to assess the consequences of consumers having less information, I increase the estimated variance of the price distributions two- and four-fold to reflect consumers knowing less about prices in the market. The results are shown as Models R3 (=doubled variance) and R4 (=quadrupled variance) in Table B4. The displayed models are equivalent to Model 1 in the article, but I report only the mean brand preferences in Table B4. I find the cost of one search to be \$80.27 when the variance is doubled and \$124.37 when the variance is quadrupled. Recall that I found cost of one search of \$36.08 for the same model specification under the assumption that consumers know the distributions of prices present in the market (Table B1). This means that search costs are increasing when consumers are less knowledgeable about the distributions of prices. The loglikelihoods of the model specifications with doubled and quadrupled variances are −3306.43 and −3303.00, respectively. The loglikelihood of the same model where I assume consumers know the distribution of prices present in the market and estimate its variance from data on premia (Model 1, Table 8) is −3214.85. Thus, my assumption appears to be more consistent with the data as compared to the alternative assumption of less information.

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