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Evaluating Search Cost Models: Estimation and Prediction*

Adrian Düll[†] Heiko Karle[‡] Simon Martin[§] Heiner Schumacher[¶]

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Abstract

The classic search models assume that consumers adhere to a particular method of search (sequential or non-sequential) and that they know the true price distribution. In this paper, we evaluate how well the search cost estimates from classic models predict search outcomes – the amount of search and purchase prices – when these assumptions are violated. To this end, we conduct an online experiment in which we vary searchers' information about the price distribution of a homogeneous good. For each treatment, we (i) estimate search costs, (ii) fit each model to the estimated search cost distribution to obtain in- and out-of-sample predictions about outcomes, and (iii) compare predicted and realized outcomes. We find that the prediction performance of each model is largely robust to violations of the informational assumption. Further, the prediction performance of the sequential and non-sequential search model are similar, despite the fact that the search environment strongly favors sequential search.

Keywords: Online Search, Search Costs, Search Cost Estimation

JEL Classification: C90, D12, D83

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1 Introduction

In many markets, consumers have to invest time and effort to acquire product and price information before making a purchase (Stigler, 1961). This informational friction potentially creates price dispersion: Some firms may charge relatively low prices in order to serve those customers who compare many prices, while other firms may charge high prices to maximize profits from customers who search only few options. A large literature in industrial organization quantifies the extent of informational frictions in markets by estimating consumers' search costs from observed prices and – if available – search behavior.[1] Given an estimated model of consumer search and firm pricing, researchers can study how changes in the market setting would affect the market equilibrium and consumer welfare.

The identification of search costs builds on the conjecture that consumers acquire additional information until the marginal costs of further search equal its marginal expected gains. There are two classic search paradigms that capture this trade-off: *sequential* and *non-sequential* (or *fixed sample size* or *simultaneous*) search. Under sequential search, the decision maker (DM) decides after each search whether to purchase the good from a previously sampled shop or to continue search. Under non-sequential search, the DM first chooses the number of shops she wants to search and, after completing the search spell, purchases the good with the lowest price (or the highest net utility) in her sample.

Both search paradigms have been used extensively in the theoretical and empirical literature on consumer search. Sequential search first has been examined by McCall (1970) and Weitzman (1979). It is used in the theoretical literature in the context of price search, for example, by Stahl (1989), Janssen et al. (2005), and most recently by Mauring and Williams (2023). Several papers including Kim et al. (2010), Kim et al. (2017), and Moraga-González et al. (2023) estimate search costs based on the sequential search paradigm. Non-sequential search has been introduced by Stigler (1961). In the theoretical literature, it is used, for example, by Burdett and Judd (1983), Janssen and Moraga-González (2004), and Atayev (2022). A lot of empirical work builds on the non-sequential search model, e.g., Moraga-González and Wildenbeest (2008), De Los Santos et al. (2012), Honka (2014), Ghose et al. (2019), Lin and Wildenbeest (2020), as well as Fischer et al. (2024).

Using the classic search paradigms to estimate search costs is not innocuous though, for two reasons. First, an important assumption in both models is that the DM knows the distribution over potential outcomes. At each stage of the search process, this distribution defines the expected gains from (further) search and hence the continuation or completion of the search spell. However, when consumers are unfamiliar with the product category, the informational

[1] Additionally, a large literature in labor economics studies jobs search and the impact of informational frictions on wages and unemployment; see Le Barbanchon et al. (2024) for a recent review of this literature.

assumption may not be satisfied. This concern is well recognized in the literature (below we describe how previous studies have relaxed the assumption of full information).

Second, it is by no means clear that all consumers follow the same search paradigm or that they follow any of these paradigms at all. Some consumers may apply sequential, others non-sequential search. They may also follow a combination of sequential and non-sequential search (Morgan and Manning, 1985). The empirical literature on consumer search finds support for both search paradigms. Alternatively, some consumers may apply heuristics such as "search sequentially, but conduct no more than *n* searches" or "conduct *n* searches, regardless of the costs and (expected) gains from search." Thus, it is not clear which empirical model researchers should use to estimate search costs. Observational data is typically not rich enough to jointly identify consumers' expectations about the price distribution, their search method, and the corresponding search costs (provided such a value is well-defined at all).

Despite these concerns, the two classic search models may be good *as-if* models. To see whether this is the case, we examine the following questions in this paper: If a researcher has estimated a distribution over search costs using one of the classic models, then how well can one reconstruct the amount of search and the prices paid by consumers from this distribution? And how well can one predict the amount of search and purchase prices under alternative price distributions? Specifically, we are interested in the answers to these questions in settings for which we know that the informational and search protocol assumptions are violated.

In order to obtain appropriate data, we consider an experimental search environment that is structured as sequential by design and where we can vary both the price distribution as well as consumers' information about the price distribution. To examine the predictive performance of a sequential and a non-sequential search model, we apply three steps for each treatment:

(i) We estimate search costs using an ordered-probit regression framework. The estimation yields us a fully specified search cost distribution.

(ii) We use a given search model, parameters of the search environment, and the estimated search cost distribution to simulate predicted search outcomes (number of searches and purchase prices). In this manner, we obtain both in- and out-of-sample predictions.

(iii) We compare the predicted and realized distributions over search outcomes in terms of means, medians, and two measures from statistics that quantify the similarity between distributions, namely *Hellinger distance* and *Kullback-Leibler divergence*.

This research design allows us to evaluate whether the classic search models have desirable as-if properties, even when we know that certain assumptions are not satisfied.[2]

In our online search experiment, we consider conditions where subjects receive information about the price distribution as well as conditions where no such information is provided. Our subjects are online workers on Amazon Mechanical Turk (AMT) and Prolific (PRO). They can search for the lowest price of a hypothetical homogeneous product in up to 100 online shops. Search creates time and hassle costs: To obtain the price quote from an online shop, they have to enter a 16-digit code. The price savings that subjects realize constitutes their payoff in the experiment. The main treatment variations are the price distribution and subjects' information about the price distribution. We consider settings with left-skewed, uniform, and right-skewed price distributions; for every price distribution there is both a treatment where the distribution is made salient to subjects and a treatment where subjects obtain no information about it. Through additional treatments, we identify the behavioral parameters in our search environment, that is, the level of context effects (the tendency that people become less sensitive to price variations of fixed size when the price level or range of prices increases) and the extent to which search costs are convex in the number of searches (e.g., due to fatigue).

We observe fairly heterogeneous search outcomes in our experiment. There is both a large fraction of subjects who do not search more than two shops and a substantial share of subjects who search more than ten shops. Accordingly, the dispersion of purchase prices is large. Neither the pure sequential nor the pure non-sequential search model is fully consistent with subjects' search behavior. All treatments exhibit a substantial degree of recall, which is inconsistent with sequential search under constant search costs. Additionally, several treatments show evidence of price-dependent search, which is inconsistent with non-sequential search.

Our first main result is that the prediction performance of both the sequential and non-sequential search model is hardly affected when the underlying assumption on consumers' information is violated. One may conjecture that the estimated search cost distribution from the classic models captures search outcomes better in settings where subjects know the true price distribution. Indeed, we find for the sequential search model that the point estimates of the prediction errors (regarding the number of searches and purchase prices) are on average smaller when subjects are informed about the price distribution than when this is not the case. However, the difference between the prediction errors is small relative to their variability. For the non-sequential search model we even find that the point estimates of the prediction errors are smaller for treatments where subjects are not informed about the price distribution.

The second main result is that the prediction performance of the non-sequential search model is fairly close to that of the sequential search model, despite the fact that the search

[2]We focus on the sequential and non-sequential search model in the main part of this paper since in most empirical search models, decision-makers are assumed to know the outcome distribution. However, in an extension, we also evaluate the predictive performance of a search without priors model based on Parakhonyak (2014).

environment is fully tailored to the sequential framework. Again, the differences in prediction errors are small relative to the variability of the prediction error point estimates. The non-sequential search model even predicts the median of search outcomes slightly better than the sequential search model. We obtain this pattern both for in- and out-of-sample predictions. Thus, despite the stark simplification assumed by the non-sequential search model, it seems to describe aggregate search outcomes fairly well, regardless of whether consumers have information about the price distribution or not. This result suggests that using the non-sequential search model in empirical work – as it is frequently done in the literature – is an appropriate choice even in settings where consumers can continue their search at any stage and are not constrained by a predetermined number of searches.

Finally, we compare the prediction performance of the classic search models to the prediction performance of models in the forecasting literature (for retail sales and inflation). Overall, we find that the sequential and non-sequential search model are good as-if models, even in settings when the underlying assumptions on the search protocol and consumers' information about the price distribution are violated. Both models capture heterogeneity in search outcomes: Lower search costs imply (in expectation) more searches and lower prices. This has implications both for empirical and theoretical research. In empirical research, neither the precise form of search nor the initial information of consumers is known very well. Our findings suggest that the key findings are expected to be robust even when these components cannot be captured precisely. Choosing the right search protocol and the level of consumer information is a challenge also in the theoretical literature. While it is clearly important to understand the implications of different search settings, our findings indicate that as far as estimated search costs are concerned, most common methods tend to be quite robust.

Related Literature. This paper continues the literature that evaluates the validity of structural models by using experiments. Bajari and Hortaçsu (2005) consider models of first-price auctions and Salz and Vespa (2020) evaluate models of dynamic competition. In the context of search, Brown et al. (2011) examine how reservation wages change over the search spell and Karle et al. (2025) identify the impact of context effects on search cost estimates. Most recently, Fong et al. (2025) consider a search experiment in order to disentangle prominence effects and biased beliefs in online shopping behavior. The present paper continues this line of research and evaluates the performance of search models when their underlying assumptions are (partially) violated.

Further, the paper contributes to the search literature that considers a relaxation of the full-information assumption. Two approaches address the issue of information in the theoretical literature. First, consumers may have a prior about the potential distributions over outcomes and update their beliefs in Bayesian manner; see, e.g., Rothschild (1974), Rosenfield and

Shapiro (1981), and Bikhchandani and Sharma (1996). These papers examine under which conditions the optimal search strategy is myopic, so that it can be characterized by a reservation value. They show that this is the case when searchers' beliefs are given by Dirichlet priors. The second approach considers search without priors: Consumers use their observations to non-parametrically estimate the distribution over outcomes, see Chou and Talmain (1993), Parakhonyak (2014), or Schlag and Zapechelnyuk (2021). The first two papers consider an updating rule that maximizes entropy and generates a piece-wise uniform belief about the distribution over outcomes. The empirical literature that estimates search costs without the full information assumption largely follows the parametric approach. Koulayev (2013), De los Santos et al. (2017), and Hu et al. (2019) assume Dirichlet priors or Dirichlet process priors; Ursu et al. (2020) and Ursu et al. (2023) use normally distributed priors. Jindal and Aribarg (2021) conduct a search experiment (with monetary search costs) in which they elicit subjects' beliefs about the price distribution after each search. They find that prior beliefs are fairly heterogeneous and that the assumption of Bayesian updating about the price distribution does not significantly bias the search cost estimates as long as researchers take this heterogeneity into account. Our paper is the first that evaluates the predictive performance of different search models in settings with varying degrees of consumer information about prices. We focus on search models that consumers are informed about the price distribution. In an extension, we also consider a model of search without priors that is based on Parakhonyak (2014).

Our paper also contributes to the literature that tests the validity of the sequential and non-sequential search paradigm in the context of consumer search. Sequential search with constant search costs implies that the DM has a constant reservation value and trades with the last sampled shop or searches all available shops. These predictions are frequently violated in experimental data, see, e.g., Brown et al. (2011) and Casner (2021). Within the empirical literature, Chen et al. (2007), De Los Santos et al. (2012), and Honka and Chintagunta (2017) test the two models against each other. Chen et al. (2007) apply a non-parametric likelihood ratio test to discriminate between the two search models (using price data from a price comparison website). They do not find significant differences between them in terms of fit. De Los Santos et al. (2012) examine web browsing data and find (for the online book market) that consumers recall shops and that there is no significant positive correlation between prices and the decision to continue search. Both observations are consistent with non-sequential search, but inconsistent with the sequential search model. Honka and Chintagunta (2017) observe consideration sets and purchases (in the U.S. auto insurance market). They find that the set of observed prices and choices is consistent with non-sequential search and that applying an empirical model that is based on sequential search would generate biased estimation results. In contrast, Bronnenberg et al. (2016) find that chosen options on average are discovered late in the search spell, which is consistent with sequential, but inconsistent with non-sequential search. Overall, the evidence from observational data generates mixed results on the validity of the two search paradigms. In the present paper, we therefore evaluate the prediction performance of both models.

The rest of the paper is organized as follows. In Section 2, we formally describe the sequential and non-sequential search model. In Section 3, we present our experimental design and procedures. In Section 4, we explain how we estimate search costs in our setting and how we evaluate the prediction performance of the two search models. In Section 5, we present the experimental results, the evaluation of the search models, and extensions of our analysis. Section 6 concludes. The Appendix contains all mathematical proofs and the instructions to the experiment. The Online Appendix contains further empirical analyses.

2 Search Models

In this section, we formally introduce the sequential and non-sequential search model. We allow for context effects and convex search costs. For each model, we state a condition for optimal search that will be used in the search cost estimation.

We consider a decision-maker who has unit demand for a homogeneous good and can search a (large) finite number N of firms that offer this good at varying prices. Each firm chooses its price p according to the distribution function F with support $[a, b] \subset [0, \infty)$ and continuously differentiable density f. The DM can search one firm at a time. Let $c(n)$ denote the time and hassle costs of n searches. We assume that $c(0) = 0$ and that c is weakly convex. If the DM purchases the good at price p after searching n firms, her (decision) utility equals

$$V^{du}(p, F, n) = u - v(p, F) - c(n) + wn, \tag{1}$$

where u is her utility from the product and w is a monetary payoff for each search. In a standard search setting, w equals zero. In the experiment, we will have treatments with positive values w, for reasons that we explain below. The function v defines how the benefits (price savings) from search are perceived relative to the physical costs of search. It may capture the standard case $v(p, F) = p$ as well as preferences with diminishing sensitivity or relative thinking as in Karle et al. (2025).

Sequential Search. We first assume that the DM searches optimally according to the random sequential search paradigm. After each search, the DM chooses between purchasing the good at the lowest price discovered so far and conducting one more search. By a simple induction argument we can show that this implies that the DM follows a reservation price policy[3]: Sup-

[3] In Appendix A.1, we present the proof of this statement.

pose the DM has searched $n-1$ firms and the smallest price discovered so far equals $\hat{p}$. Then there is a value r_n so that it is optimal for the DM to stop search and to purchase the good at price $\hat{p}$ if $\hat{p} < r_n$, and to conduct the n'th search if $\hat{p} \geq r_n$. This reservation price is defined by the indifference condition

$$c(n) - c(n-1) = \int_a^{r_n} (v(r_n, F) - v(p, F)) f(p) dp + w. \tag{2}$$

The left-hand side of this equation represents the cost of the n'th search and the right-hand side the benefits from search, i.e., the expected gains from learning one more price.

Non-sequential Search. Next, we assume that the DM searches optimally according to the non-sequential search paradigm. She chooses (and commits to) the number n of price quotes she wishes to obtain. After completing n searches, she trades with the firm in her sample that offers the product at the lowest price. The distribution of this price is given by

$$F(p; n) = 1 - (1 - F(p))^n. \tag{3}$$

Therefore, the expected expenses weighted by function v are equal to

$$\mathbb{E}(v; n) = \int_a^b v(p, F) n(1 - F(p))^{n-1} f(p) dp. \tag{4}$$

The DM chooses the number $n \leq N$ of searches that maximizes her expected payoff

$$u - \mathbb{E}(v; n) - c(n) + wn. \tag{5}$$

Note that the expected expenses $\mathbb{E}(v; n)$ decrease, while search costs $c(n)$ increase in the number of searches n. The DM searches n shops only if

$$-\mathbb{E}(v; n) - c(n) + wn \geq -\mathbb{E}(v; n') - c(n') + wn' \tag{6}$$

for any number $n' \leq N$ of searches.

Empirical Predictions. The two search models make different empirical predictions about the relationship between the DM's purchase decision and the sequence of observed prices as well as about the relationship between observed prices and the DM's decision to continue search. De Los Santos et al. (2012), Honka and Chintagunta (2017), and Karle et al. (2025) use such predictions to examine whether consumer search is consistent (or inconsistent) with sequential and non-sequential search. We follow this approach and consider three tests on whether recall behavior and the price-dependency of search are in line with a given search model. To formulate these tests, we assume that there is an infinite population of DMs who can search a (large) finite number of firms. Further, we assume that there is a positive fraction of DMs in this population who search at least one firm and a positive fraction of DMs who search at least two firms. The first test considers recall.

Test 1 (Recall)**.** *Consider the identity of the shop from which a DM purchases the product.*

(a) If all DMs search sequentially and the costs per search are constant in the number of searches, every DM buys the product from the last sampled shop or searches all shops.

(b) If all DMs search non-sequentially, then among those who search n shops the probability of purchase from a given sampled shop is $\frac{1}{n}$.

If marginal search costs are constant in the number of searches, then under sequential search, a DM will not recall a previously sampled shop, unless she has searched all shops. This prediction has been discussed repeatedly in the literature; see, for example, Brown et al. (2011) and De Los Santos et al. (2012). However, recall of previously sampled shops is possible under sequential search if marginal search costs are convex in the number of searches. We obtain a stronger test for non-sequential search. Independent of the search cost function, recall should take place with probability $\frac{n-1}{n}$ if a DM searches n shops. The next test considers the link between observed prices and the decision to continue search.

Test 2 (Price-Dependence I)**.** *Consider the correlation between the price at the first sampled shop and the decision to continue search.*

(a) If all DMs search sequentially, this correlation is positive.

(b) If all DMs search non-sequentially, this correlation is zero.

The sequential search model implies a reservation price policy. Therefore, it would generate a positive correlation between prices and the decision to continue search. In contrast, under non-sequential search, the number of searched shops is chosen ex-ante so that there is no such correlation. This is also reflected in the last test.

Test 3 (Price-Dependence II)**.** *Consider the correlation between the price at the current shop and the decision to continue search.*

(a) If all DMs search sequentially, this correlation is positive.

(b) If all DMs search non-sequentially, this correlation is zero.

3 Experimental Design and Procedures

We design an online search experiment in which we vary both the price distribution as well as subjects' information about the price distribution. We will use the experimental data to estimate search costs and evaluate the extent to which search outcomes (number of searches and purchase prices) can be recovered from these estimates. In the following, we describe the design of our baseline treatment, treatment variations, and experimental procedures.

Experimental Design Baseline Treatment. We invite subjects (on Amazon Mechanical Turk and Prolific) to an online experiment which consists of two parts. The first part is a survey in which we elicit demographic information (age, gender, education) as well as measures of cognitive ability, risk preferences, trust, and online labor supply on the platform. After the survey, we describe the second part, which consists of an experimental search task. Screenshots of the instructions and the search task are shown in Appendix A.5.

In the search task, subjects have to buy a fictitious product that we call "product A." They can search for the lowest price of this product in up to 100 shops. The price at each shop (in USD) is drawn from a uniform distribution on the interval $[a, b] = [3.00, 6.00]$. This distribution is shown to subjects, both in the instructions and on the screen where they conduct price search. If they purchase product A at price p, their payoff from the search task equals $b - p$. Upon entering the search screen they can also push a button to indicate that they do not want to search at all. In this case, their payoff from the search task is zero.

To see the price of an online shop, subjects have to enter a 16-digit code. We disable the copy-and-paste option so that subjects have to write it down on some device or take a picture before entering it on the next screen. The code varies between shops and subjects. After discovering the price at a shop, subjects see an overview with all prices discovered so far. They can then purchase product A at any previously sampled shop (by clicking on the corresponding price) or continue the search spell. Hence, recall is essentially for free. If a subject wishes to purchase product A at a price that is not the smallest one discovered so far, a warning message occurs with the offer to purchase it at the lowest available price (this offer can be declined). In the first part of the experiment, subjects have to enter an example code so that they are informed about the physical costs of search.

Treatment Variation. We implement ten different treatments that we classify in four treatment types: *information*, *no-information*, *piece rate*, and *scale treatments*. In the following, we explain each type of treatment and the objective behind the treatment variation.

We implement three *information treatments* in which we vary the price distribution. The first information treatment is the baseline treatment and denoted by $S1.0$. The other two information treatments are identical to the baseline treatment (including the support of the price distribution), except that the price distributions in these treatments are either skewed to the left (more probability mass on high prices) or skewed to the right (more probability mass on low prices). Figure 1 displays the two distributions. We call these two treatments $S1.0 - l$ and $S1.0 - r$, respectively.

Next, we have three *no-information treatments* which are identical to the information treatments $S1.0$, $S1.0 - l$, and $S1.0 - r$, except that subjects do not receive any information about the price distribution, neither in the instructions nor on the search screen. They are informed that the highest price at each shop is $b = 6.00$ USD and we explicitly state in the instructions that no further information about the price distribution is provided. We call these treatments $S1.0 -$ noinfo, $S1.0 - l$.noinfo, and $S1.0 - r$.noinfo, respectively.

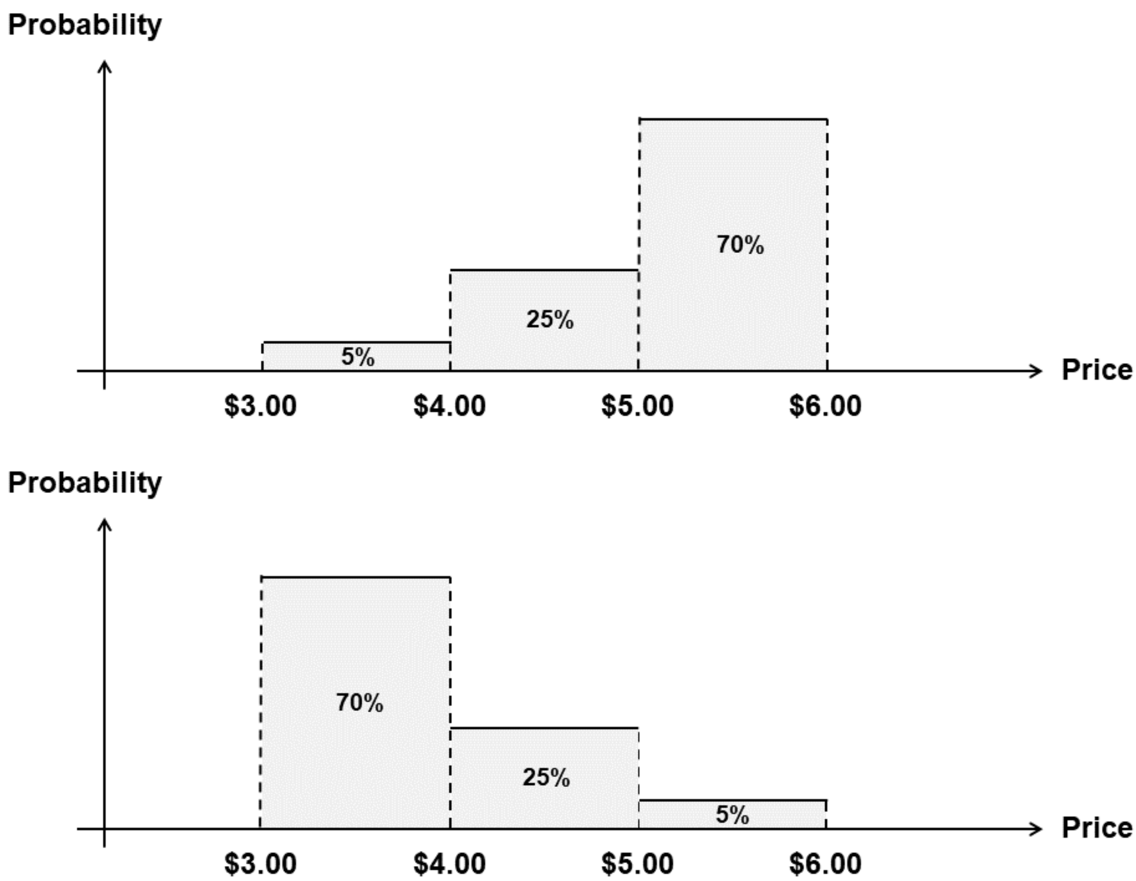

Figure 1: Left-skewed price distribution in treatment $S1.0 - l$ (upper graph) and right-skewed price distribution in treatment $S1.0 - r$ (lower graph). These graphs were also shown in the experimental instructions as well as on the search screen during the experiment.

Further, we implement three piece rate treatments. They are identical to the baseline treatment, except that the price interval is $[0.2a, 0.2b] = [0.60, 1.20]$ and that subjects earn a positive amount w for each shop that they search, in addition to the realized price savings. We implement piece rate treatments with $w = 0.04$ USD, $w = 0.08$ USD, and $w = 0.12$ USD, and we denote these treatments by $S0.2 - pr4$, $S0.2 - pr8$, and $S0.2 - pr12$, respectively. The instructions to the experiment are the same as in the baseline treatment; only on the last screen we announce that, in addition to the gains from search, subjects would earn the amount w for each completed search.

With the piece rate treatments we can identify the shape of the search cost function c. Note that search incentives vanish as searchers sequentially find smaller prices. Therefore, we would need a lot of observations (to get sufficiently many unlucky searchers who find low prices only at later searches) if we rely on search incentives alone to identify the level of convexity of c, especially when $c(n)$ increases only slowly in the number of searches n.

Finally, we have one *scale treatment*. It is identical to the baseline treatment except that the price interval is $[5.0a, 5.0b] = [15.00, 30.00]$ USD instead of $[a, b]$ USD. We denote this treatment by $S5.0$. The potential gains from search are larger in the scale treatment than in the baseline treatment. With the scale treatment we can identify the shape of function v, that is, subjects' perception of the gains from search relative to the physical cost of search.

Experimental Procedures. In the first part of the experiment, we measure subjects' cognitive ability, willingness to take risk, and trust.[4] Further, we measure online labor supply by asking subjects about their expected hourly earnings and about how many hours per week they spend working on the online platform (Amazon Mechanical Turk or Prolific) on average. Before subjects can commence price search, they have to answer a comprehension question.[5] We programmed the experimental software with oTree (Chen et al., 2016) and run the experiment with online workers from Amazon Mechanical Turk (AMT) as well as with subjects from Prolific (PRO). Specifically, we run the treatments $S0.2 - pr4$, $S0.2 - pr8$, $S0.2 - pr12$, $S5.0$, $S1.0$, and $S1.0 -$ noinfo on AMT in November 2023, and the treatments $S1.0 - l$, $S1.0 - r$, $S1.0 - l$.noinfo, and $S1.0 - r$.noinfo with both AMT workers and Prolific subjects in June 2024. Before starting the experiment, we pre-registered it on the AEA RCT Registry (registry number AEARCTR-0012497) and obtained IRB approval from the Board for Ethical

[4]We measure cognitive ability through a cognitive reflection test. We elicit the general willingness to take risk as in Dohmen et al. (2011) by asking the question: *Do you generally avoid taking risks or are you a risk-taker?* This question has to be answered on a scale between zero (not at all willing to take risks) and ten (very willing to take risks). To elicit trust, we ask the standard question from the world values survey: *Generally speaking, would you say that you need to be very careful in dealing with people or that most people can be trusted?* The response of this question has to be provided on a scale between zero (people cannot be trusted at all) and ten (people can fully be trusted).

[5]Specifically, we ask the following question: *Suppose that after searching two times for the lowest price, a shopper buys Product A for USD [70 percent of the maximal price in the treatment]. What will be the shopper's bonus?* Subjects have to choose the answer from a list of four possible options. If they indicate the wrong answer, we explain to them how to find the correct value and they get a second chance to provide the correct response. All subjects are admitted to the search task.

Questions in Science of the University of Innsbruck. In the pre-registration, we indicate that we exclude subjects from the final sample who (i) do not search at least one shop and also do not indicate that they do not want to search at all (by pressing the corresponding button on the search screen) as well as subjects who (ii) conduct at least one search, but who do not purchase the product at the lowest observed price.[6]

Table 1: Demographic Variables and Labor Supply

Sample, Treatment	N	Share Females	Age	Average hourly Earnings	Average hours per Week
Information and No-Information Treatments					
AMT $S\,1.0$	213	0.441	34.88 (10.09)	12.62 (14.10)	35.90 (18.29)
AMT $S\,1.0$ – noinfo	210	0.419	35.66 (10.32)	11.41 (13.40)	34.49 (20.62)
AMT $S\,1.0 - l$	202	0.431	33.42 (8.75)	11.17 (12.70)	38.00 (22.75)
AMT $S\,1.0 - l$.noinfo	192	0.385	34.31 (9.33)	11.41 (13.28)	38.01 (21.06)
AMT $S\,1.0 - r$	199	0.342	34.89 (9.59)	11.29 (14.02)	39.88 (25.53)
AMT $S\,1.0 - r$.noinfo	209	0.340	35.04 (9.39)	10.76 (13.39)	38.24 (21.48)
PRO $S\,1.0 - l$	115	0.591	39.84 (13.63)	8.57 (4.65)	11.00 (8.74)
PRO $S\,1.0 - l$.noinfo	134	0.530	38.90 (12.12)	8.77 (5.97)	10.82 (8.52)
PRO $S\,1.0 - r$	152	0.605	37.55 (12.24)	8.14 (3.90)	11.33 (8.27)
PRO $S\,1.0 - r$.noinfo	161	0.590	39.43 (12.55)	7.62 (4.06)	10.98 (8.82)
Piece Rate and Scale Treatments					
AMT $S\,0.2 - pr4$	216	0.407	34.55 (10.04)	11.71 (12.74)	34.60 (18.08)
AMT $S\,0.2 - pr8$	202	0.396	34.99 (9.81)	13.44 (14.20)	33.38 (18.57)
AMT $S\,0.2 - pr12$	194	0.418	35.37 (10.64)	12.57 (13.08)	35.35 (18.03)
AMT $S\,5.0$	190	0.416	34.57 (10.34)	11.94 (12.88)	35.26 (22.54)

Notes: Standard deviation in parentheses. Age in years, average hourly earnings in USD.

We recruited 1301 subjects in November 2023 and 859 subjects in June 2024 on AMT; 76 subjects of the former sample and 57 subjects of the latter were excluded according to our pre-registered rules. On Prolific, 566 subjects participated in our experiment in June 2024 and four of them were excluded. Table 1 provides an overview of our samples. While there are a few differences between our three samples (the November 2023 sample, the June 2024 AMT

[6]For organizational reasons, the experiment on Prolific differed from the one on AMT in two details: First, Prolific subjects earn 2.00 USD for the completion of the first part of the experiment and an additional bonus of 0.10 USD for completing the search task (regardless of how many shops they search). Second, Prolific subjects have to complete the search task right after finishing the first part of the experiment, while AMT workers have three days for searching (since almost all AMT workers start searching right away, it is unlikely that this difference matters for our results).

sample, and the June 2024 Prolific sample), each of these samples is balanced in terms of demographic variables, labor supply, as well as education and personal characteristics (cognitive ability, willingness to take risks, and trust); see Appendix A.6. In particular, this holds for each pair of information and no-information treatment with the same price distribution.[7]

AMT Workers and Prolific Subjects. We briefly comment on the two subject pools. Both of them have been used extensively for research. They also have been subject of controversies regarding data quality and reliability (especially AMT workers). We observe from Table 1 that AMT workers spend more time per week on AMT than Prolific subjects on the Prolific platform. Indeed, Eyal et al. (2022) suggest that between 30 and 42 percent of AMT workers state that working on AMT is their main source of income, compared to only 4 to 8 percent on Prolific. Some researchers interpret AMT workers as "professional survey takers" (Chandler et al., 2014). In the context of our research question, this is unproblematic as it implies that the opportunity costs of time are well-defined for these subjects.

A major concern regarding AMT workers is that they score low on comprehension (Eyal et al., 2022). However, similar shares of AMT workers and Prolific subjects correctly answer the comprehension check at the end of the instructions: 73.4 percent of the November 2023 AMT sample[8], 84.8 percent of the June 2024 AMT sample, and 79.2 percent of the June 2024 Prolific sample. Another major concern regarding data from AMT is that many responses may originate from "bots." We use *Google*'s reCAPTCHA and we request subjects to enter a 16-digit example code that is displayed as a picture (without the copy and paste option). We believe that these two measures filter out any potential non-human participants. Further, we monitor code input times during the search task. We did not detect any anomalies that would lead us to believe that some participants were not actual human subjects.

4 Search Cost Estimation and Evaluation

4.1 Search Cost Estimation

We derive the empirical search models from the search paradigms of Section 2. For this, we have to specify the shape of the function v and the shape of the search cost function c. To parametrize context effects, we assume

$$v(p, F) = \frac{p}{(\max\{1, \Delta_F\})^{\rho}}, \tag{7}$$

[7]The only exception is that the CRT score differs between treatments in the November 2023 AMT sample.

[8]This number excludes AMT workers in the piece-rate treatments who faced a more complex comprehension check question (as their payoff comes from two sources).

where $\Delta_F = b - a$. This function captures relative thinking of degree ρ. A similar function has been used by Somerville (2022) to quantify the extent of relative thinking. Relative thinking of degree $\rho = 0$ implies $v(p, F) = p$ so that the DM takes absolute price savings fully into account (as in most empirical search models), while $\rho = 1$ implies scale-independent search behavior: This means that the DM exerts the same search effort, regardless of whether all prices (and hence price savings) are scaled up by some factor $z > 1$ or not. Based on the results from Karle et al. (2025) we expect that our estimate of ρ is close to one. Next, to parametrize the cost function, we follow DellaVigna and Pope (2018) and assume the functional form

$$c(n) = \frac{kn^{1+\kappa}}{1+\kappa}, \tag{8}$$

where $\kappa \geq 0$. The value $\kappa = 0$ implies that search costs are constant in the number of searches, as it is frequently assumed in theoretical search models; $\kappa > 0$ captures convex marginal search costs. We expect that the estimated value of κ is close to zero. There is no time pressure in the experimental task and the task difficulty remains constant over time. Further, the time needed to identify a price quote (around one minute) is fairly small compared to the average time subjects work on AMT and Prolific, see Table 1. Therefore, a significant level of convexity would be difficult to reconcile with the labor supply on these platforms.

Sequential Search. We first outline how we estimate search costs assuming optimal sequential search. Suppose we know that the DM searches n shops and that her reservation value at the n'th shop equals r_n. For given parameter values ρ, κ and a uniform distribution F on the interval $[a, b]$ with $\Delta_F \geq 1$ we can derive her search cost parameter k from equation (2) as

$$k^{\text{seq}}(r_n, \rho, \kappa, n) = \frac{1+\kappa}{n^{1+\kappa} - (n-1)^{1+\kappa}} \left(\frac{1}{\Delta_F^{\rho}} \frac{(r_n - a)^2}{2(b-a)} + w \right). \tag{9}$$

In Appendix A.2, we generalize this term to the left- and right-skewed price distributions in our experiment. Since we do not observe the reservation price r_n directly, we have to derive it from the discovered prices. For this, we assume that DM i's search cost parameter k_i is drawn from a lognormal distribution G_i, truncated at t. To ensure that all observed outcomes can be rationalized through search costs drawn from G, we set the truncation point $t = 3 \max_i k^{seq}(p_i^1, \rho, \kappa, n_i)$ during the estimation. Let x_i be observable characteristics of DM i. The log of DM i's search cost parameter k_i is then given by the equation

$$\ln k_i = x_i\beta + \sigma\varepsilon_i, \tag{10}$$

where ε_i follows a standard normal distribution Φ, β is a vector of parameters affecting the mean of the underlying normal distribution, and σ is the standard deviation of the underlying normal distribution, see Appendix A.3 for computational details. For each DM i with number of searches $n_i \in \{2, ..., 99\}$, we observe the two smallest prices p_i^1, p_i^2 discovered before the DM purchased the product. The reservation price r_n must be located in the interval $[p_i^1, p_i^2]$. For given parameters ρ and κ, we obtain the likelihood contribution

$$\begin{aligned} P_i &= \Pr(k^{\mathrm{seq}}(p_i^1, \rho, \kappa, n_i) \leq k_i < k^{\mathrm{seq}}(p_i^2, \rho, \kappa, n_i)) \\ &= \left[\Phi\left(\frac{\ln k^{\mathrm{seq}}(p_i^2, \rho, \kappa, n_i) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln k^{\mathrm{seq}}(p_i^1, \rho, \kappa, n_i) - x_i\beta}{\sigma}\right)\right] \Phi\left(\frac{\ln t - x_i\beta}{\sigma}\right)^{-1}. \end{aligned} \tag{11}$$

For censored observations with $n_i = 1$ or $n_i = N$, we adjust the likelihood contribution accordingly; see Appendix A.2. Adding up the logarithm of these terms for all subjects yields the log-likelihood function for maximum likelihood estimation. We then use the treatments with variation in scales to identify context effects ρ, and those with variation in the piece rates to identify κ. Given these, we obtain the treatment-specific parameters of the respective search cost distributions.

Non-sequential Search. Next, we describe how we estimate search costs assuming optimal non-sequential search. Consider a DM who plans to search $n \geq 1$ shops. For given parameter values ρ, κ and a uniform distribution F on the interval $[a, b]$ with $\Delta_F \geq 1$, her expected expenses can be calculated from equation (4) as

$$\mathbb{E}^{[n]}(v) = \frac{1}{\Delta_F^{\rho}}\left(a + \frac{b-a}{n+1}\right). \tag{12}$$

In Appendix A.2, we derive the corresponding term for left- and right-skewed price distribution, respectively. From the fact that the DM weakly prefers searching n shops to searching $n+1$ shops we obtain a lower bound on the search cost parameter k from equation (6):

$$k_-^{\mathrm{nseq}}(\rho, \kappa, n) = \frac{1+\kappa}{(n+1)^{1+\kappa} - n^{1+\kappa}}\left(\mathbb{E}^{[n]}(v) - \mathbb{E}^{[n+1]}(v) + w\right). \tag{13}$$

Similarly, we obtain an upper bound on k from the fact that the DM weakly prefers searching n shops to searching $n-1$ shops:

$$k_+^{\mathrm{nseq}}(\rho, \kappa, n) = \frac{1+\kappa}{n^{1+\kappa} - (n-1)^{1+\kappa}}\left(\mathbb{E}^{[n-1]}(v) - \mathbb{E}^{[n]}(v) + w\right). \tag{14}$$

Let the number of searches of DM i be given by n_i. For given parameters ρ and κ, the true value of the search cost parameter k_i for DM i must be in the interval between $k_-^{\mathrm{nseq}}(\rho, \kappa, n_i)$ and $k_+^{\mathrm{nseq}}(\rho, \kappa, n_i)$. Assuming that the log of search costs is normally distributed, we obtain the likelihood contribution

$$\begin{aligned} P_i &= \Pr(k_-^{\text{nseq}}(\rho,\kappa,n_i) \le k_i < k_+^{\text{nseq}}(\rho,\kappa,n_i)) \\ &= \left[\Phi\left(\frac{\ln k_+^{\text{nseq}}(\rho,\kappa,n_i) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln k_-^{\text{nseq}}(\rho,\kappa,n_i) - x_i\beta}{\sigma}\right)\right]\Phi\left(\frac{\ln t - x_i\beta}{\sigma}\right)^{-1}. \end{aligned} \tag{15}$$

For censored observations we adjust the likelihood contribution accordingly; see Appendix A.2. As for the sequential search model, we estimate ρ from the treatments with scale variation, and subsequently the treatment-specific search cost distribution parameters. However, the parameter κ is not identified under non-sequential search due to the interaction of the piece rate w and the number of searches n. Thus, we impute the value of κ that we obtain from the sequential search model also to the non-sequential search setting.

4.2 Evaluation of Search Cost Estimates

Each estimation procedure generates a fully specified distribution over search costs. This distribution can be inserted back into the search model to obtain predictions about the amount of search and realized purchase prices. This allows us to evaluate the validity of the search cost estimates by comparing predicted and realized outcomes in the experiment.

We proceed as follows: Let $\hat{G}$ be any given estimated distribution over the cost parameter k. For any given value k and price distribution F, we calculate (or numerically approximate) the probability distribution over the number of searches n and purchase price p, for each of the search models. In Appendix A.4, we derive the analytical expressions assuming $\kappa = 0$ and $w = 0$. Integrating over $\hat{G}$ we derive the predicted distribution over the number of searches, $\hat{G}^{[1]}(n)$ for $n \in \{0, 1, ..., 100\}$ and the predicted distribution over purchase prices $\hat{G}^{[2]}(p)$ for $p \in \{3.00, 3.01, ..., 6.00\}$.[9] Let $\hat{g}^{[1]}$ and $\hat{g}^{[2]}$ be the corresponding densities. Accordingly, define by $G^{[1]}$ and $G^{[2]}$ the realized distributions over the number of searches and purchase prices, respectively, with densities $g^{[1]}$ and $g^{[2]}$.

First, we consider the difference in means (and medians) between realized and predicted distribution for each information and no-information treatment. We call this difference *prediction error in means (medians)*.[10] To quantify the variability of the point estimate of the

[9] We numerically approximate the integral over $\hat{G}$ by obtaining 1000 simulation draws from the estimated search cost distribution.

[10] The literature on prediction accuracy and "Wisdom of the Crowd" also frequently uses the term *mean absolute error (MAE)* for this value; see, for example, König-Kersting et al. (2025).

prediction error in means, we use the standard error, as defined by

$$\mathrm{SE} = \sqrt{\frac{\sigma^2_{G^{[j]}}}{l_{G^{[j]}}} + \frac{\sigma^2_{\hat{G}^{[j]}}}{l_{\hat{G}^{[j]}}}} \tag{16}$$

for $j \in \{1, 2\}$, where $\sigma_{G^{[j]}}$ is the standard deviation of the realized values of variable j (number of searches or purchase prices) and $l_{G^{[j]}}$ is the number of observations in the considered treatment. Further, $\sigma_{\hat{G}^{[j]}}$ is the is the standard deviation in a sample of 1,000 random draws from the predicted distribution $\hat{G}^{[j]}$ (thus, the value $l_{\hat{G}^{[j]}}$ equals 1,000).

Next, we evaluate how close the realized and predicted distribution are to each other. There exist various methods to measure the similarity of probability distributions. In our context, the most convenient way to quantify how close two distributions are to each other is the Hellinger distance (HD). For the discrete distributions $G^{[1]}$ and $\hat{G}^{[1]}$, it is defined as

$$H(G^{[1]}, \hat{G}^{[1]}) = \frac{1}{\sqrt{2}} \sqrt{\sum_{n \in \{0,1,\dots,100\}} \left(\sqrt{g^{[1]}(n)} - \sqrt{\hat{g}^{[1]}(n)} \right)^2}, \tag{17}$$

and for the distributions $G^{[2]}$ and $\hat{G}^{[2]}$, it is given by

$$H(G^{[2]}, \hat{G}^{[2]}) = \frac{1}{\sqrt{2}} \sqrt{\sum_{p \in \{3.00,3.01,\dots,6.00\}} \left(\sqrt{g^{[2]}(p)} - \sqrt{\hat{g}^{[2]}(p)} \right)^2}. \tag{18}$$

The Hellinger distance takes on values between zero and one, where the value zero indicates that the two distributions are identical and the value one is attained when there is no overlap in the support of the two distributions. In addition to the Hellinger distance, we report the Kullback-Leibler (KL) divergence. For the discrete distributions $G^{[1]}$ and $\hat{G}^{[1]}$, it is defined as

$$D_{KL}(G^{[1]} \parallel \hat{G}^{[1]}) = \sum_{n \in \{0,1,\dots,100\}} g^{[1]}(n) \log\left(\frac{g^{[1]}(n)}{\hat{g}^{[1]}(n)} \right). \tag{19}$$

This value can be interpreted as the amount of additional "surprise" if one expects the distribution to be $\hat{G}^{[1]}$ when the true distribution is given by $G^{[1]}$. For the distributions $G^{[2]}$ and $\hat{G}^{[2]}$, the KL divergence is given by

$$D_{KL}(G^{[2]} \parallel \hat{G}^{[2]}) = \sum_{p \in \{3.00,3.01,\dots,6.00\}} g^{[2]}(p) \log\left(\frac{g^{[2]}(p)}{\hat{g}^{[2]}(p)} \right). \tag{20}$$

The KL divergence is not a metric like the Hellinger distance. It does neither satisfy symmetry nor the triangle inequality.

5 Results

We present our results as follows. In Subsection 5.1, we provide the descriptive statistics of search behavior and outcomes in our experiment. In Subsection 5.2, we examine the extent to which subjects' search behavior is consistent with the search models. In Subsection 5.3, we present the results from search cost estimation for each model. In Subsection 5.4 we evaluate how well the search cost estimates capture the outcomes from search in-sample and out-of-sample. In Subsection 5.5, we briefly discuss two extensions: the estimation and evaluation of a search without priors model and the evaluation of search models according to an alternative outcome variable. In Subsection 5.6, we compare the prediction performance of all models.

5.1 Descriptive Statistics

We describe the search behavior in our experiment and compare the outcomes from search between treatments with and without information about the price distribution. To identify a price quote, subjects need on average 64.3 seconds (sd = 35.4) in the November 2023 AMT sample, 59.1 seconds (sd = 27.6) in the June 2023 AMT sample, and 56.6 seconds (sd = 34.0) in the June 2023 Prolific sample.[11] The differences in the mean search time are significant between the three samples (t-test p-values < 0.059), but there are no statistically significant differences between the treatments of any given sample (ANOVA p-value > 0.238).

Table 2 provides an overview of subjects' search behavior and search outcomes in our experiment. It shows the share of searchers (subjects who search at least one shop), the mean and median number of searches, as well as the mean and median purchase price (the purchase price is set to b for subjects who do not search at all). In the last column, Table 2 shows the p-values of two-sided t-tests which examine whether there is a statistically significant difference in the number of searches (or the realized purchase price) between a given information treatment and the corresponding no-information treatment with the same price distribution.

We make four important observations from Table 2. First, the share of searchers is fairly large, between 91.7 and 100.0 percent, so most subjects conduct at least one search. There are mostly no significant differences in the share of searchers between a given information treatment and its corresponding no-information treatment (t-test p-values > 0.050). Thus, whether or not subjects obtain information about the price distribution does not seem to matter for their decision to commence price search.

Second, if we compare the information treatment AMT $S\,1.0$ and the scale treatment AMT $S\,5.0$, we observe that the amount of search is fairly similar in these two treatments, despite the

[11] To obtain these values we excluded searches that took more than 5 minutes.

Table 2: Average Search Outcomes

Sample Treatment	Share Searchers	Mean and Median No. Searches		Mean and Median Purchase Price		Diff. p-value
Information and No-Information Treatments						
AMT $S\,1.0$	0.972	10.49 (21.13)	2	3.76 (0.88)	3.40	0.344/0.705
AMT $S\,1.0$ – noinfo	0.957	12.49 (22.12)	3	3.79 (0.89)	3.39	
AMT $S\,1.0 - l$	0.980	20.56 (28.22)	10	4.07 (0.88)	3.92	0.849/0.225
AMT $S\,1.0 - l$.noinfo	1.000	20.02 (27.73)	8	4.18 (0.91)	4.07	
AMT $S\,1.0 - r$	0.975	13.78 (22.83)	4	3.41 (0.64)	3.14	0.970/0.483
AMT $S\,1.0 - r$.noinfo	0.995	13.70 (22.61)	5	3.37 (0.52)	3.16	
PRO $S\,1.0 - l$	0.922	6.35 (6.47)	4	4.43 (0.74)	4.29	0.132/0.574
PRO $S\,1.0 - l$.noinfo	0.918	8.22 (11.87)	5	4.37 (0.82)	4.28	
PRO $S\,1.0 - r$	0.954	2.97 (3.26)	2	3.60 (0.68)	3.37	0.000/0.028
PRO $S\,1.0 - r$.noinfo	0.963	6.55 (7.78)	4	3.44 (0.62)	3.24	
Piece Rate and Scale Treatments						
AMT $S\,0.2 - pr4$	0.917	16.68 (32.09)	2	0.81 (0.21)	0.72	–
AMT $S\,0.2 - pr8$	0.970	23.28 (37.75)	2	0.76 (0.18)	0.69	
AMT $S\,0.2 - pr12$	0.974	18.96 (34.17)	2	0.77 (0.19)	0.69	
AMT $S\,5.0$	0.974	10.55 (20.09)	2	18.94 (4.73)	16.52	

Notes: Standard deviation in parentheses. The first (second) p-value in the last column originates from a two-sided t-test which compares the mean number of searches (purchase price) between an information treatment and the no-information treatment with the same price distribution.

fact that search incentives are five times larger in the latter than in the former treatment. This suggests that the context effect parameter ρ should be around one, meaning that subjects use relative price differences to balance the gains and losses from search rather than absolute price differences. The search cost estimation in Subsection 5.3 will confirm this conjecture. Thus, the extent of context effects in our experiment is consistent with those documented for AMT workers and Prolific subjects in Karle et al. (2025).

Third, the availability of information about the price distribution has mostly no effect on the average number of searches and purchase prices. For four out of five pairs of information and no-information treatments we do not find significant differences in the number of searches or purchase prices. Only for the Prolific treatment pair $S\,1.0 - r$ and $S\,1.0 - r$.noinfo we observe that subjects search more and on average realize lower purchase prices when they are not informed about the price distribution. The differences are significant at least on the 5-percent level. In all other treatments, subjects on average realize roughly the same gains from search, regardless of whether they know the price distribution or not.

Fourth, subjects react to the price distribution: They search more shops if the price distribution is left-skewed (more probability mass on high prices) than if it is right-skewed (more probability mass on low prices). Combining the data from the information and no-information treatments, this effect is significant for both the AMT (t-test p-value < 0.001) and the Prolific sample (t-test p-value < 0.001). There are also significant differences in the realized purchase prices, but this effect is of course (in part) driven by the different price distributions. We conclude that the amount of search and realized purchase prices are relatively unresponsive to the availability of price distribution information, but responsive to the price distribution.

5.2 Empirical Predictions: Results

We briefly summarize the results of the empirical tests from Section 2. The detailed results can be found in Appendix A.7. There is a substantial amount of recall in our experiment: At least 29.7 percent of subjects recall a previously sampled shop (without having searched all shops) in a given treatment. There is also a significant level of price-dependency of search in six out of ten treatments: The probability of search spell continuation tends to increase in the price of the last sampled shop. The former observation is inconsistent with sequential search (with constant search costs), while the latter observation is inconsistent with non-sequential search. We find few systematic differences between information and no-information treatments. Overall, the important observation here is that none of the considered search models is fully consistent with subjects' search behavior in all treatments.

5.3 Search Cost Estimation: Results

We estimate search costs according to the procedures outlined in Section 4. Table 3 shows the estimation results for the sequential and Table 4 for the non-sequential search model.

Sequential Search. We first estimate search costs assuming that there are no context effects ($\rho = 0$) and that the marginal search costs are constant ($\kappa = 0$), see specification (1) in Table 3. We apply this model to the treatments $S5.0$, $S1.0$, and $S1.0 -$ noinfo from AMT. As expected, the estimated coefficients (which govern the respective search cost estimates for these treatments) are different between treatment $S5.0$ and the other two treatments. Specifically, the estimated mean search cost for treatment $S5.0$ is 2.09 USD per search, compared to 1.01 USD and 0.92 USD per search in treatment $S1.0$ and treatment $S1.0 -$ noinfo, respectively. Recall that subjects exert roughly the same search effort in all these treatments. The difference in search costs between treatments is significant (p-values < 0.001), which indicates that we need to take context effects into account to obtain realistic search cost estimates.

Table 3: Search Cost Estimates: Sequential Search

	(1)	(2)	(3)	(4)	(5)
$S5.0$	-0.67*		-2.94***		
	(0.28)		(0.39)		
$S1.0$	-2.35***		-2.42***		
	(0.23)		(0.40)		
$S1.0$ – noinfo	-2.54***		-2.75***		
	(0.23)		(0.38)		
$S1.0 - l$				-3.92***	-3.14***
				(0.22)	(0.19)
$S1.0 - l$.noinfo				-3.83***	-3.37***
				(0.22)	(0.18)
$S1.0 - r$				-4.43***	-2.81***
				(0.22)	(0.18)
$S1.0 - r$.noinfo				-4.42***	-4.21***
				(0.21)	(0.16)
β		-1.81***			
		(0.16)			
σ	2.87***	2.47***	3.37***	2.65***	1.87***
	(0.12)	(0.12)	(0.20)	(0.09)	(0.07)
κ		0.00			
		(0.03)			
ρ		1.00***			
		(0.00)			
Data	AMT	AMT	AMT	AMT	PRO
Treatments	$S5.0$	$S5.0$	$S5.0$	$S1.0 - l$	$S1.0 - l$
	$S1.0$	$S1.0$	$S1.0$	$S1.0 - r$	$S1.0 - r$
	$S1.0$ – noinfo	$S1.0 - pr4$	$S1.0$ – noinfo	$S1.0 - l$.noinfo	$S1.0 - l$.noinfo
		$S1.0 - pr8$		$S1.0 - r$.noinfo	$S1.0 - r$.noinfo
		$S1.0 - pr12$			
ρ est.	fixed 0	est.	fixed at est.	fixed at est.	fixed at est.
κ est.	fixed 0	est.	fixed at est.	fixed at est.	fixed at est.
Observations	613	1015	613	802	562
Log.Lik.	-1230.89	-2451.85	-1205.23	-1613.49	-1061.22
AIC	2469.79	4911.70	2418.46	3236.99	2132.44
BIC	2487.46	4931.39	2436.13	3260.42	2154.10
SC $S5.0$	2.093		0.161		
	(3.972)		(0.291)		
SC $S1.0$	1.009		0.185		
	(2.709)		(0.310)		
SC $S1.0$ – noinfo	0.915		0.169		
	(2.567)		(0.298)		
SC $S1.0 - l$				0.130	0.149
				(0.298)	(0.285)
SC $S1.0 - l$.noinfo				0.136	0.127
				(0.306)	(0.258)
SC $S1.0 - r$				0.100	0.184
				(0.258)	(0.322)
SC $S1.0 - r$.noinfo				0.101	0.067
				(0.259)	(0.172)

Notes: Ordered probit regressions with truncation for the sequential search model. In the top panel, standard errors of the estimated parameters are in parentheses. The bottom panel presents the search cost estimates for each treatment, derived from the parameter estimates shown in the top panel. The first value represents the mean of the implied search cost distribution, with the standard deviation of the distribution provided in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4: Search Cost Estimates: Non-Sequential Search

	(1)	(2)	(3)	(4)	(5)
$S5.0$	0.20		-1.77***		
	(0.28)		(0.46)		
$S1.0$	-1.89***		-1.70***		
	(0.22)		(0.45)		
$S1.0-$ noinfo	-2.23***		-2.26***		
	(0.21)		(0.41)		
$S1.0-l$				-3.80***	-3.07***
				(0.22)	(0.16)
$S1.0-l$.noinfo				-3.63***	-3.27***
				(0.23)	(0.15)
$S1.0-r$				-3.99***	-2.54***
				(0.22)	(0.15)
$S1.0-r$.noinfo				-4.09***	-3.74***
				(0.21)	(0.14)
β		-1.89***			
		(0.14)			
σ	2.79***	2.32***	3.40***	2.72***	1.67***
	(0.12)	(0.10)	(0.22)	(0.10)	(0.06)
ρ		1.00***			
		(0.00)			
Data	AMT	AMT	AMT	AMT	PRO
Treatments	$S5.0$	$S5.0$	$S5.0$	$S1.0-l$	$S1.0-l$
	$S1.0$	$S1.0$	$S1.0$	$S1.0-r$	$S1.0-r$
	$S1.0-$ noinfo	$S1.0-pr4$	$S1.0-$ noinfo	$S1.0-l$.noinfo	$S1.0-l$.noinfo
		$S1.0-pr8$		$S1.0-r$.noinfo	$S1.0-r$.noinfo
		$S1.0-pr12$			
ρ est.	fixed 0	est.	fixed at est.	fixed at est.	fixed at est.
Observations	613	1015	613	802	562
Log.Lik.	-1865.28	-3121.28	-1831.91	-2729.22	-1550.10
AIC	3738.57	6248.55	3671.83	5468.45	3110.20
BIC	3756.24	6263.32	3689.50	5491.88	3131.86
SC $S5.0$	2.841		0.215		
	(4.575)		(0.332)		
SC 1.0	1.227		0.219		
	(2.991)		(0.334)		
SC $S1.0-$ noinfo	1.034		0.192		
	(2.723)		(0.316)		
SC $S1.0-l$				0.141	0.138
				(0.314)	(0.257)
SC $S1.0-l$.noinfo				0.153	0.120
				(0.327)	(0.233)
SC $S1.0-r$				0.129	0.202
				(0.299)	(0.324)
SC $S1.0-r$.noinfo				0.123	0.081
				(0.292)	(0.180)

Notes: Ordered probit regressions with truncation for the non-sequential search model. In the top panel, standard errors of the estimated parameters are in parentheses. The bottom panel presents the search cost estimates for each treatment, derived from the parameter estimates shown in the top panel. The first value represents the mean of the implied search cost distribution, with the standard deviation of the distribution provided in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

We identify the level of context effects ρ from the variation in scales (i.e., the treatments $S1.0$ and $S5.0$) and possible non-linearities in marginal search costs κ from the piece-rate treatments $S0.2 - pr4$, $S0.2 - pr8$, and $S0.2 - pr12$, see specification (2) in Table 3. The estimated values of ρ and κ are 1.00 and 0.00, respectively. Hence, the level of context effects in our setting is comparable to that in Karle et al. (2025). Next, we re-estimate search costs for the treatments $S5.0$, $S1.0$, and $S1.0 -$ noinfo from AMT, using the estimated values $\rho = 1.00$ and $\kappa = 0.00$, see specification (3) in Table 3. The estimated mean search costs for all treatments are now relatively close to each other, between 0.16 USD and 0.19 USD per search. The differences in search costs between these treatments are not significant (p-values > 0.273).

Using the estimated values $\rho = 1.00$ and $\kappa = 0.00$, we estimate search costs for the June 2024 AMT and Prolific samples, see specification (4) and (5), respectively, in Table 3. In the AMT sample, the estimated mean search costs are similar between treatments, varying from 0.10 USD to 0.14 USD. There are no significant differences between a given information treatment and the no-information treatment with the same price distribution (p-values > 0.760). In the Prolific sample, estimated mean search costs vary between 0.07 USD and 0.18 USD. There is no significant difference between the estimated search costs in PRO $S1.0 - l$ and PRO $S1.0 - l$.noinfo (p-value $= 0.373$). However, the difference in estimated search costs is statistically significant for PRO $S1.0 - r$ and PRO $S1.0 - r$.noinfo (p-value < 0.001). This is the only pair of information and no-information treatment in our samples where subjects' search behavior depends on the availability of price information.

Non-Sequential Search. We consider the same specifications for non-sequential search as for the sequential search model, see Table 4. The only difference is that we take $\kappa = 0$ as given, since the parameter κ is not identified under non-sequential search due to the interaction of the piece rate w and the number of searches n. We again obtain a level of context effects of $\rho = 1.00$. The search cost estimates are somewhat larger for non-sequential than for sequential search. In the November 2023 AMT sample, they vary between 0.19 USD and 0.22 USD; the difference between the information and the no-information treatment is not statistically significant (p-value $= 0.224$). In the June 2024 AMT sample, search costs vary between 0.12 USD and 0.15 USD; the difference between a given information treatment and the no-information treatment with the same price distribution is again not significant (p-values $>$ 0.561). Finally, in the June 2024 PRO sample, search costs vary between 0.08 USD and 0.20 USD. Here the difference in search costs is not significant between PRO $S1.0 - l$ and PRO $S1.0 - l$.noinfo (p-value $= 0.397$), while the difference between PRO $S1.0 - r$ and PRO $S1.0 - r$.noinfo is statistically significant (p-value < 0.001).

Direct Search Costs. In Appendix A.8, we compare these search cost estimates to subjects' opportunity costs of time (which we elicit through the first part of the experiment). It turns out that estimated search costs are roughly in line with subjects' opportunity costs of time.

Goodness-of-Fit Measures. Before we evaluate the prediction performance of our search models, we briefly consider their goodness of fit through the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). These goodness of fit measures attempt to resolve the problem of model overfitting by introducing a penalty term for the number of parameters in the model.[12] All else equal, the preferred model is the one with the minimal AIC (or BIC) value. Tables 3 and 4 show for each model the AIC and BIC values. For a given specification and sample, the log-likelihood for the sequential search model is larger than that of the non-sequential search model (the number of parameters is identical for these models). Both AIC and BIC suggest that the sequential search model better fits the data.

5.4 Evaluation of Search Cost Estimates: Results

How well do the search cost estimates from the classic search models capture subjects' search outcomes in-sample and out-of-sample? In this subsection, we examine the prediction performance of the search models by following the procedure outlined in Subsection 4.2. For a given treatment, we obtain the distribution $\hat{G}$ over the search cost parameter k from the search cost estimation. Given this distribution, we derive, for each treatment, a predicted distribution $\hat{G}^{[1]}$ over the number of searches and a predicted distribution $\hat{G}^{[2]}$ over purchase prices. Then, for any treatment combination, we compute the absolute distance in means and medians between the predicted and realized distributions, $\hat{G}^{[1]}/G^{[1]}$, $\hat{G}^{[1A]}/G^{[1A]}$, and $\hat{G}^{[2]}/G^{[2]}$, as well as the corresponding values of Hellinger distance and Kullback-Leibler divergence.

Table 5 presents the results in aggregated form. For in-sample predictions, we average how well the prediction from a given treatment captures behavior in the same treatment. For out-of-sample predictions, we average how well the prediction from a given treatment captures outcomes in other treatments from the same experimental sample. The detailed results can be found in Online Appendix B.1. Figure A1 to Figure A4 in the Appendix display in-sample predictions and outcomes graphically for each treatment. They are helpful for putting the numbers from Table 5 into context.

[12] Let h be the number of estimated parameters in the model, ξ the number of data points, and $\hat{L}$ the maximized value of the likelihood function for the model. We then have $AIC = 2h - 2\ln\hat{L}$ and $BIC = h\ln\xi - 2\ln\hat{L}$.

Table 5: Predicted versus Observed Distribution over Outcomes

	Prediction Error		Difference predicted and realized distribution	
	Means (SE)	Medians	HD	KL
Number of Searches				
sequential search (in-sample)				
information treatments	1.84 (1.32)	1.40	0.30	0.27
no-information treatments	2.52 (1.48)	1.70	0.32	0.33
all treatments	2.18 (1.40)	1.55	0.31	0.30
non-sequential search (in-sample)				
information treatments	2.47 (1.31)	0.60	0.31	0.30
no-information treatments	1.79 (1.48)	0.30	0.33	0.36
all treatments	2.13 (1.39)	0.45	0.32	0.33
sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	2.83 (1.41)	1.85	0.32	0.33
any treatment → any treatment	3.43 (1.38)	1.87	0.32	0.33
non-sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	2.86 (1.39)	1.25	0.34	0.38
any treatment → any treatment	3.84 (1.36)	1.42	0.33	0.36
Purchase Prices				
sequential search (in-sample)				
information treatments	0.05 (0.06)	0.07	0.33	0.33
no-information treatments	0.09 (0.06)	0.10	0.32	0.32
all treatments	0.07 (0.06)	0.09	0.32	0.32
non-sequential search (in-sample)				
information treatments	0.16 (0.06)	0.08	0.36	0.39
no-information treatments	0.07 (0.06)	0.04	0.32	0.30
all treatments	0.12 (0.06)	0.06	0.34	0.34
sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.09 (0.06)	0.09	0.33	0.32
any treatment → any treatment	0.13 (0.06)	0.14	0.33	0.33
non-sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.15 (0.06)	0.09	0.35	0.37
any treatment → any treatment	0.14 (0.06)	0.09	0.35	0.37

Notes: Average differences between predicted and observed distribution, as outlined in Subsection 4.2. The detailed values for each treatment combination are presented in Table B1 to Table B4 in the Online Appendix.

In-Sample Predictions. We first examine whether the sequential and the non-sequential search model capture search outcomes better when subjects have full information about the price distribution compared to the case when they do not have any information about the price distribution. One may hypothesize that the prediction performance of these models is higher when subjects are informed about the price distribution.

Let us first consider the sequential search model. The average prediction error in means in the information treatments is 1.84 for number of searches and 0.05 for purchase prices. The prediction error is slightly higher in the no-information treatments: Here the average prediction error in means is 2.52 for number of searches and 0.09 for purchase prices. We observe a similar pattern for the prediction error in means, Hellinger distance, and Kullback-Leibler divergence.

However, given the variability of the point estimates of the prediction errors in means, the difference in prediction performance seems small. The value in parentheses next to the prediction error in means is the average standard error (SE) for the prediction error. For every pair of information and no-information treatment we find that the prediction error in means for the latter treatment is well within the 95-percent confidence interval of the prediction error in means for the former treatment.

Next, we consider the non-sequential search model. Here the pattern for the prediction performance is reversed. In the information treatments, the average prediction error in means is 2.47 for number of searches and 0.16 for purchase prices. In contrast, in the no-information treatments, the average prediction error in means is only 1.79 for number of searches and 0.07 for purchase prices. In terms of prediction error in means, Hellinger distance, and Kullback-Leibler divergence, we mostly see a similar pattern. Again, the difference in prediction performance is modest as the prediction error in means of any information treatment is within the 95-percent confidence interval of the prediction error in means of the corresponding no-information treatment (and vice versa).

Interestingly, if we take the average prediction performance over both information and no-information treatments, the sequential and the non-sequential search model perform similarly well, both for number of searches and purchase prices. In terms of prediction error in medians, the non-sequential search model is even slightly better than the sequential search model. This result is remarkable for (at least) two reasons. First, we chose the experimental design so that the search task is as close as possible to the sequential search model. Second, as discussed in Subsection 5.3, the model fit in the regression is strictly better for the sequential than for the non-sequential search model.

Out-of-Sample Predictions. We further examine how well the search cost estimates from one treatment predict the search outcomes in other treatments. We do this in two steps. First, we use the distribution over the search cost parameter from a given information (no-information) treatment and use it to derive the prediction for the no-information (information) treatment with the same price distribution. The values for "inf./no-inf. → no-inf./inf." in Table 5 show the corresponding prediction error in means and medians as well as the distribution distance measures. Second, we take any combination of information and/or no-information treatments from the November 2023 AMT sample, any combination of information and/or no-information treatments from the June 2024 AMT sample, and any combination of information and/or no-information treatments from the June 2024 PRO sample to compare out-of-sample predictions and realized outcomes. In the tables, the corresponding prediction errors are displayed in the lines labeled "any treatment → any treatment."

As one may expect, the precision of the out-of-sample predictions is slightly worse than the precision of the in-sample predictions; one can see that from comparing the out-of-sample predictions to the in-sample predictions that take all treatments into account. However, the differences in prediction quality are modest, given the overall variability of prediction errors. This holds for all search models and all outcome variables.

Consistent with the in-sample predictions, we observe that the sequential search model produces slightly more precise out-of-sample predictions than the non-sequential search model in terms of prediction error in means, Hellinger distance, and Kullback-Leibler divergence. Taking all treatments together, the average prediction error in means for the number of searches is 3.43 for the sequential search model and 3.84 for the non-sequential search model; the average prediction error in means for purchase prices is 0.13 USD for the sequential search model and 0.14 USD for the non-sequential search model. In terms of prediction error in medians, the non-sequential search model is slightly better than the sequential search model. Again, the differences in the prediction performance between the two models is fairly modest.

5.5 Search without Priors and Restricted Number of Searches

We briefly consider two extensions of our analysis. First, we apply our method to a search model where consumers do not have priors about the price distribution, but estimate the price distribution based on their price observations. We examine how well the search cost estimates from this model predict search outcomes in the information and no-information treatments. Second, we evaluate the prediction performance of our search models according to another outcome variable, the *restricted number of searches*.

Search without Priors. We consider a model of search without priors, building on Parakhonyak (2014). In this model, the DM does not know the price distribution F and has no prior about it. Instead, she estimates the price distribution from observed prices. Let

$$p^{[n]} = (p^{1,n}, p^{2,n}, ..., p^{n,n}) \tag{21}$$

be the ordered set of observed prices after n searches, where $p^{1,n}$ is the lowest and $p^{n,n}$ the highest price observed so far. We set $p^{[0]} = \varnothing$. The DM knows the upper bound of the support of the price distribution b and assumes that the lower bound equals θb with $\theta < 1$. If $\theta = \frac{a}{b}$, the DM has the correct belief about the support of the price distribution F. Throughout, we assume that $\theta \leq \frac{a}{b}$ so that there are no surprises for the DM. After n searches, the DM applies the quantile preserving estimation procedure from Chou and Talmain (1993) and Parakhonyak (2014) to form beliefs about the price distribution:

(i) she assigns equal probability mass $\frac{1}{1+n}$ to each interval $[\theta b, p^{1,n}]$, $[p^{1,n}, p^{2,n}]$,..., $[p^{n,n}, b]$ when these prices are different; she distributes the probability mass uniformly within each interval.

(ii) she assigns probability mass $\frac{\xi-1}{n+1}$ to a price that appears ξ times in the sample.

Denote by $\hat{F}^{[n]}(p \mid p^{[n]})$ the DM's belief about the price distribution F after n searches if the set of observed prices is given by $p^{[n]}$. Accordingly, $\hat{F}^{[0]}(p \mid p^{[0]})$ is the uniform distribution on the interval $[\theta b, b]$. The estimator $\hat{F}^{[n]}$ is consistent, i.e., for $n \to \infty$ it converges uniformly to the true price distribution; see Chou and Talmain (1993). Under the proposed estimation procedure the DM conducts the n'th search if

$$c(n) - c(n-1) \leq \int_{\theta b}^{p^{1,n-1}} (v(p^{1,n-1}, \hat{F}^{[n-1]}) - v(p, \hat{F}^{[n-1]}))\frac{1}{p^{1,n-1} - \theta b}\frac{1}{n}dp + w. \tag{22}$$

Thus, the DM's reservation price r_n^{swp} at the n'th search is implicitly defined by

$$c(n) - c(n-1) = \int_{\theta b}^{r_n^{\text{swp}}} (v(r_n^{\text{swp}}, \hat{F}^{[n-1]}) - v(p, \hat{F}^{[n-1]}))\frac{1}{r_n^{\text{swp}} - \theta b}\frac{1}{n}dp + w. \tag{23}$$

Note that the reservation price r_n^{swp} depends on the set of observed prices $p^{[n-1]}$ only through the function v that captures context effects. If this function is independent of $p^{[n-1]}$, then also r_n^{swp} is independent of $p^{[n-1]}$.

We estimate search costs based on the search without priors model and evaluate it according to the same measures as the classic search models in the previous subsection, see Online Appendix B.2 for details. One may conjecture that the search without priors model performs better in the no-information than in the information treatments. However, this is not what we find. In the information treatments, the average prediction error in means is 2.09 for number of searches and 0.05 for purchase prices. In contrast, in the no-information treatments, the average prediction error in means is 2.57 for number of searches and 0.07 for purchase prices. The other measures mostly confirm that the prediction performance of the search without priors model is, if anything, slightly worse for the no-information treatments.

The prediction performance of the search without priors model is similar to that of the classic search models according to most indicators. For in-sample predictions, the average prediction error in means is 2.33 for number of searches and 0.06 for purchase prices (these values were 2.18 and 0.07 for the sequential search model; 2.13 and 0.12 for the non-sequential search model). For out-of-sample predictions, the average prediction error in means is 4.30 for number of searches and 0.15 for purchase prices (these values were 3.43 and 0.13 for the sequential search model; 3.83 and 0.14 for the non-sequential search model). Thus, the search without priors model performs similarly as the classic search models, but there does not seem to be a strong reason for using this model instead of the others.

Restricted Number of Searches. In empirical applications of search models, the number of shops is typically much smaller than 100. It therefore may be important to know how many individuals search only one or two shops (or do not search at all) and how many individuals search more than that. To capture this information in succinct manner, we compute for each observation the *restricted number of searches*. This value equals 0, 1, 2, 3, or "4 or more", where the last value is assigned if a subject searched four or more shops. We then apply the same steps as outlined in Subsection 4.2 to calculate the prediction error in means and medians as well as the Hellinger distance and Kullback-Leibler divergence with respect to this variable.

Online Appendix B.3 shows the detailed results. We find that the prediction performance of the two classic search models for the restricted number of searches is slightly better in the information than in the no information treatments. Again, the differences in prediction error in means are small relative to the variability of the point estimates. Further, the non-sequential search model exhibits smaller prediction errors in means and medians than the sequential search model. However, the latter model better captures the distribution over outcomes according to the Hellinger distance and Kullback-Leibler divergence. Overall, both models perform similarly well in predicting the distribution over the restricted number of searches.

5.6 How well do search models predict the outcomes from search?

There does not exist an objective benchmark to which we can easily compare the predictive performance of search models. In order to provide some perspective on the prediction quality of our search cost estimates, we perform the following two steps. First, we consider the *relative prediction error in means (medians)* in- and out-of sample for all search models and outcome variables. This value is defined as the prediction error divided by the realized value.[13] It allows us to compare the prediction performance across models and domains. Second, we compare the relative prediction error of our models to relative prediction errors taken from the literature on predictions of sales and macroeconomic variables (inflation).

Table 6: Relative Prediction Error

	Number of Searches		Rest. Number of Searches		Purchase Prices	
	Mean	Median	Mean	Median	Mean	Median
In-Sample Predictions						
sequential search	0.209	0.310	0.101	0.208	0.018	0.023
non-sequential search	0.189	0.125	0.050	0.083	0.032	0.017
search without priors	0.189	0.140	0.036	0.050	0.017	0.013
Out-of-Sample Predictions						
sequential search	0.389	0.353	0.120	0.234	0.032	0.036
non-sequential search	0.386	0.337	0.100	0.173	0.037	0.025
search without priors	0.416	0.419	0.126	0.226	0.039	0.034

Notes: Differences between predicted and observed values (mean and median), relative to the the realized value.

Table 6 shows the relative prediction error in means and medians for all models and outcome variables. The predictions of the number of searches tend to be quite noisy with relative prediction errors up to around 40 percent. The predictions of the restricted number of searches are substantially less noisy, and the predictions of purchase prices are quite accurate, with relative prediction errors of less than 4 percent. There is no search model that strictly dominates the others (or that is strictly dominated by another model). The non-sequential search model performs fairly well, despite the fact that the search setting favors the sequential search model.

Table 7 displays the relative prediction errors for several examples taken from the forecasting literature. This literature is fairly diverse and reports different measures of prediction accuracy. We selected examples for which we can compute the relative prediction error based on the data provided in the paper. The prediction of retail sales based on neural networks (Alon et al., 2001) is fairly precise with a relative prediction error of 1.5 to 2.8 percent, while the prediction of inflation year-on-year is more noisy with a relative prediction error of 25.9

[13]Here is an example: The average number of searches in treatment AMT $S1.0$ is 10.49, the prediction error in means of the sequential search model for this treatment is 1.48. Hence, the relative prediction error in means of the sequential search model for the number of searches in treatment AMT $S1.0$ is $\frac{1.48}{10.49} \approx 0.141$.

percent. Compared to these values, the predictions of the search models hold up well, especially in the domain of purchase prices (where our relative prediction errors are between 1.7 and 3.9 percent).

Table 7: Relative Prediction Error: Examples for Sales and Macro Variables

Variable	Method	Study/Data	Relative Prediction Error
Market shares	expert prediction market	Matzler et al. (2013)	0.075 to 0.575
Individual product sales	statistical and AI forecasting models	Aras et al. (2017)	0.139 to 0.513
Aggregate retail sales	neural network forecasting models	Alon et al. (2001)	0.015 to 0.028
Inventory	stat. forecasting with expert judgment	Trapero et al. (2013)	0.059
US Inflation, one year ahead	macroeconomic model	Federal Reserve economic data[14]	0.259

6 Conclusion

In this paper, we examined the extent to which the classic search models – sequential and non-sequential search – are good as-if models. How well do the search cost estimates from these models capture the outcomes from search, especially in settings where the underlying assumptions on consumers' information about prices or their search method are violated? To address this question, we conducted an online search experiment in which we manipulated the price distribution as well as subjects' knowledge about the price distribution. For each treatment, we estimated search costs, fitted each model to the estimated search cost distribution to obtain predictions about the amount of search and purchase prices, and then compared the predicted and realized distributions over search outcomes.

Our main results are two-fold. First, we found that the predictive performance of the sequential search model is slightly higher in settings in which consumers know the price distribution than in settings where this is not the case. For the non-sequential search models, it is the

[14] Own calculations. Time horizon: 01/1983 to 08/2024. Data for the one-year-ahead expected inflation series was obtained from https://fred.stlouisfed.org/series/EXPINF1YR. Data for the realized year-over-year inflation rates was obtained from https://fred.stlouisfed.org/series/MEDCPIM159SFRBCLE.

other way around. In both cases, however, the differences in predictive performance between settings with and without price information are modest. Second, we found that the predictive performance of the non-sequential search model is close to that of the sequential search model, despite the fact that our search environment strongly favors sequential search. Overall, the predictive performance of the classic search models (as summarized in Table 6) indicates that the these models are decent as-if models even when their assumptions on consumer information and the search protocol are violated.

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A Appendix

A.1 Optimal Sequential Search with Convex Search Costs

We prove that equation (2) characterizes optimal sequential search when the cost function c is weakly convex. The proof proceeds by induction. Let p_N^{min} be the smallest price discovered after $N-1$ searches and let p_N be the price discovered at the N'th search. Suppose the DM has searched $N-1$ shops so far. Let r_N be defined by equation (2). By definition, it is then optimal for the DM to search the N'th shop if $p_N^{min} \geq r_N$, and to stop search otherwise. Next, suppose the DM has searched $N-2$ shops so far and let r_{N-1} be given by equation (2). Since $v(p, F)$ is strictly increasing in p, we must have $r_{N-1} \leq r_N$. Obviously, it is optimal to search shop $N-1$ if $p_{N-1}^{min} \geq r_{N-1}$. Thus, assume that $p_{N-1}^{min} < r_{N-1}$. We show that it is then optimal for the DM not to search shop $N-1$. Note that $r_{N-1} \leq r_N$ implies $p_{N-1}^{min} < r_N$. If the DM searches shop $N-1$ and discovers a price $p_{N-1} > r_N$, then, by the DM's optimal behavior at the N'th shop, it is optimal for her to stop search because $p_N^{min} = p_{N-1}^{min} < r_N$. If the DM searches shop $N-1$ and discovers a price $p_{N-1} \leq r_N$, we have $\min\{p_{N-1}, p_{N-1}^{min}\} < r_N$. Again, by the DM's optimal behavior at the N'th shop, it is optimal for her to stop search. Thus, in any case, searching shop $N-1$ would be the last search if $p_{N-1}^{min} < r_{N-1}$. By the definition of r_{N-1}, it therefore cannot be optimal to search shop $N-1$ if $p_{N-1}^{min} < r_{N-1}$, which completes the proof.

A.2 Derivation of Search Costs from Search Behavior

Search cost parameter k for sequential search and skewed distributions. We generalize equation (9) to left- and right-skewed distributions as we have them in the experiment. Suppose the distribution F is piece-wise constant and has support $[a, b]$. Let there be three intervals, $l = 1, 2, 3$, that partition $[a, b]$. The first interval is given by $[a, d_1) = [d_0, d_1)$, the second interval by $[d_1, d_2)$, and the third interval by $[d_2, b] = [d_2, d_3]$. The density in interval l is given by $f^{[l]}$. If the reservation price is located in the first interval, $l^* = 1$, the search cost parameter k equals

$$k^{\text{seq}}(r_n, \rho, \kappa, n) = \frac{1+\kappa}{n^{1+\kappa} - (n-1)^{1+\kappa}} \left(\frac{f^{[1]}(r_n - a)^2}{2\Delta_F^\rho} + w \right), \tag{24}$$

and if the reservation price is located in interval $l^* \in \{2, 3\}$, parameter k is given by

$$\begin{aligned} k^{\text{seq}}(r_n, \rho, \kappa, n) &= \frac{1+\kappa}{n^{1+\kappa} - (n-1)^{1+\kappa}} \\ &\quad \times \left(\sum_{l=1}^{l^*-1} \frac{f^{[l]}(d_l - d_{l-1})(r_n - \frac{1}{2}(d_l + d_{l-1}))}{\Delta_F^\rho} + \frac{f^{[l^*]}(r_n - d_{l^*-1})^2}{2\Delta_F^\rho} + w \right). \end{aligned} \tag{25}$$

Likelihood contributions for sequential search and censored observations. We define the likelihood contributions for censored observations in the sequential search model. If subject i searches $n_i = 0$ times, her likelihood contribution is given by

$$P_i = 1 - \Phi\left(\frac{\ln k^{\text{seq}}(b, \rho, \kappa, 1) - x_i\beta}{\sigma}\right). \tag{26}$$

Here we set $n_i = 1$ so that this expression is well-defined. If she searches $n_i = 1$ times, her likelihood contribution equals

$$P_i = \Phi\left(\frac{\ln k^{\text{seq}}(b, \rho, \kappa, 1) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln k^{\text{seq}}(p_i^1, \rho, \kappa, 1) - x_i\beta}{\sigma}\right), \tag{27}$$

and if she searches all shops, $n_i = N$, her likelihood contribution is given by

$$P_i = \Phi\left(\frac{\ln k^{\text{seq}}(b, \rho, \kappa, N) - x_i\beta}{\sigma}\right). \tag{28}$$

Search cost parameter k for non-sequential search and skewed distributions. We generalize equation (12) to left- and right-skewed distributions as we have them in the experiment. Note that with our parametrization of relative thinking we can rewrite equation (4) as

$$\mathbb{E}^{[n]}(v) = \frac{1}{\Delta_F^\rho}\left(a + \int_a^b (1 - F(p))^n dp\right). \tag{29}$$

Let F be the piece-wise constant distribution as defined above. We then have $F(p) = (p-a)f^{[1]}$ for $p \in [a, d_1)$; $F(p) = (d_1 - a)f^{[1]} + (p - d_1)f^{[2]}$ for $p \in [d_1, d_2)$; and $F(p) = (d_1 - a)f^{[1]} + (d_2 - d_1)f^{[2]} + (p - d_2)f^{[3]}$ for $p \in [d_2, b]$. With this, we can write equation (29) as

$$\begin{aligned}\mathbb{E}^{[n]}(v) \;=\; & \frac{1}{\Delta_F^\rho}\Bigg(a + \int_a^{d_1}(1 + af^{[1]} - pf^{[1]})^n dp + \int_{d_1}^{d_2}(1 + af^{[1]} - d_1 f^{[1]} + d_1 f^{[2]} - pf^{[2]})^n dp \\ & + \int_{d_2}^{b}(1 + af^{[1]} - d_1 f^{[1]} + d_1 f^{[2]} - d_2 f^{[2]} + d_2 f^{[3]} - pf^{[3]})^n dp\Bigg),\end{aligned} \tag{30}$$

which can be simplified to

$$\begin{aligned}\mathbb{E}^{[n]}(v) \;=\; & \frac{1}{\Delta_F^\rho}\Bigg(a + \frac{1}{f^{[1]}}\frac{1}{n+1}\left[1 - (1 - (d_1 - a)f^{[1]})^{n+1}\right] \\ & + \frac{1}{f^{[2]}}\frac{1}{n+1}\left[(1 - (d_1 - a)f^{[1]})^{n+1} - (1 - (d_1 - a)f^{[1]} - (d_2 - d_1)f^{[2]})^{n+1}\right] \\ & + \frac{1}{f^{[3]}}\frac{1}{n+1}(1 - (d_1 - a)f^{[1]} - (d_2 - d_1)f^{[2]})^{n+1}\Bigg).\end{aligned} \tag{31}$$

Using this expression in the equations (13) and (14) yields the search cost parameter k for non-sequential search and skewed distributions.

Likelihood contributions for non-sequential search and censored observations. We define the likelihood contributions for censored observations in the non-sequential search model. If subject i searches $n_i = 0$ times, her likelihood contribution is given by

$$P_i = 1 - \Phi\left(\frac{\ln k_{-}^{\text{nseq}}(\rho, \kappa, 0) - x_i\beta}{\sigma}\right), \tag{32}$$

and if she searches all shops, $n_i = N$, her likelihood contribution is assumed to be

$$P_i = \Phi\left(\frac{\ln k_{+}^{\text{nseq}}(\rho, \kappa, N) - x_i\beta}{\sigma}\right). \tag{33}$$

Here we cannot distinguish between subjects who wish to search exactly N shops and subjects who would search more than N shops. This distinction is, however, immaterial for our results.

A.3 Computational Details for Truncated Lognormal Distribution

Given that search costs are lognormally distributed and truncated at t, the distribution of the search cost parameter k_i of subject i is given by

$$G_i(k_i) = \Phi\left(\frac{\ln k_i - x_i\beta}{\sigma}\right)\Phi\left(\frac{\ln t - x_i\beta}{\sigma}\right)^{-1} \tag{34}$$

and the associated density function equals

$$g_i(k_i) = \frac{1}{k_i\sigma}\phi\left(\frac{\ln k_i - x_i\beta}{\sigma}\right)\Phi\left(\frac{\ln t - x_i\beta}{\sigma}\right)^{-1}, \tag{35}$$

where Φ and ϕ denote the CDF and the PDF of the standard normal distribution, respectively. The expected value of k_i is obtained through

$$\mathbb{E}(k_i) = \frac{1}{\sigma}\int_0^t \phi\left(\frac{\ln k_i - x_i\beta}{\sigma}\right)dk_i \times \Phi\left(\frac{\ln t - x_i\beta}{\sigma}\right)^{-1} \tag{36}$$

and the median through

$$med(k_i) = \exp\left(\mu + \sqrt{2}\sigma\,\text{erf}^{-1}\left(\Phi\left(\frac{\ln t - x_i\beta}{\sigma}\right) - 1\right)\right) = \exp\left(\mu + \sigma\Phi^{-1}\left(\frac{1}{2}\Phi\left(\frac{\ln t - x_i\beta}{\sigma}\right),\right)\right) \tag{37}$$

where erf^{-1} denotes the inverse of the Gauss error function.

A.4 Computations for the Evaluation of Search Cost Estimates

We derive for each search model the distribution over the number of searches and purchase prices for given search cost parameter k. Throughout we assume that $\kappa = 0$ and $w = 0$. For convenience, we write r for the reservation price (instead of r_n). Further, for any skewed (piece-wise constant) price distribution we define $F^{[1]}(r) = (r-a)f^{[1]}$ for $r \in [a, d_1)$; $F^{[2]}(r) = (d_1 - a)f^{[1]} + (r - d_1)f^{[2]}$ for $r \in [d_1, d_2)$; and $F^{[3]}(r) = (d_1 - a)f^{[1]} + (d_2 - d_1)f^{[2]} + (r - d_2)f^{[3]}$ for $r \in [d_2, b]$.

A.4.1 Computations for the Sequential Search Model

Derivation of the distribution over the number of searches for given search cost parameter k, uniform price distribution. We derive the distribution over the number of searches from equality (9). We obtain an upper bound $\bar{k}$ for the search cost parameter when we set the reservation price equal to the highest possible price, $r = b$:

$$\bar{k} = \frac{1}{\Delta_F^\rho} \frac{b-a}{2}. \tag{38}$$

It is optimal for the DM to not conduct any search if $k \geq \bar{k}$ and to conduct at least one search if $k < \bar{k}$. From equality (9) we get that, if $k < \bar{k}$, then the reservation price is given by

$$r = a + \sqrt{2k\Delta_F^\rho (b-a)}. \tag{39}$$

At a given reservation price $r < b$, the probability that the number of searches equals $n < 100$ is given by $\Pr(n) = F(r)(1-F(r))^{n-1}$ and the probability that the number of searches is $n = 100$ is given by $\Pr(n = 100) = (1 - F(r))^{99}$. Using equation (39) and the fact that F is the uniform distribution, we obtain

$$\Pr(n; k) = \sqrt{\frac{2k\Delta_F^\rho}{b-a}} \left(1 - \sqrt{\frac{2k\Delta_F^\rho}{b-a}}\right)^{n-1} \tag{40}$$

for $n < 100$ and

$$\Pr(n = 100; k) = \left(1 - \sqrt{\frac{2k\Delta_F^\rho}{b-a}}\right)^{99}. \tag{41}$$

This constitutes the distribution over the number of searches for given cost parameter k.

Derivation of the distribution over the number of searches for given search cost parameter k, skewed price distribution. We derive the distribution over the number of searches for a skewed price distribution from equations (24) and (25). To this end, we derive three boundary values from these equations:

$$\bar{k}_1 = \frac{1}{\Delta_F^\rho}\frac{f^{[1]}(d_1 - d_0)^2}{2}, \tag{42}$$

$$\bar{k}_2 = \frac{1}{\Delta_F^\rho}\left[f^{[1]}(d_1 - d_0)\left(d_2 - \frac{d_1 + d_0}{2}\right) + \frac{f^{[2]}(d_2 - d_1)^2}{2}\right], \tag{43}$$

$$\bar{k}_3 = \frac{1}{\Delta_F^\rho}\left[f^{[1]}(d_1 - d_0)\left(d_3 - \frac{d_1 + d_0}{2}\right) + f^{[2]}(d_2 - d_1)\left(d_3 - \frac{d_2 + d_1}{2}\right) + \frac{f^{[3]}(d_3 - d_2)^2}{2}\right]. \tag{44}$$

If $k < \bar{k}_1$, we have $r \in [a, d_1)$ and the DM's reservation price is defined by equality (24); if $\bar{k}_1 \leq k < \bar{k}_2$, we have $r \in [d_1, d_2)$ and the reservation price is defined by equality (25) for $l^* = 2$; if $\bar{k}_2 \leq k < \bar{k}_3$, we have $r \in [d_2, b)$ and the reservation price is defined by equality (25) for $l^* = 3$; and if $k \geq \bar{k}_3$, it is optimal for the DM not to conduct any search. We derive the reservation price for the three former cases. If $k < \bar{k}_1$, the reservation price equals

$$r = a + \sqrt{\frac{2k\Delta_F^\rho}{f^{[1]}}}. \tag{45}$$

If $\bar{k}_1 \leq k < \bar{k}_2$, it is given by

$$r = \frac{d_1 f^{[2]} - (d_1 - d_0)f^{[1]} + \sqrt{(d_1 - d_0)^2 f^{[1]}(f^{[1]} - f^{[2]}) + 2f^{[2]}k\Delta_F^\rho}}{f^{[2]}}. \tag{46}$$

If $\bar{k}_2 \leq k < \bar{k}_3$, the reservation price is given by

$$r = \frac{d_2 f^{[3]} - (d_1 - d_0)f^{[1]} - (d_2 - d_1)f^{[2]} + \sqrt{((d_1 - d_0)f^{[1]} + (d_2 - d_1)f^{[2]} - d_2 f^{[3]})^2 + f^{[3]}A}}{f^{[3]}}. \tag{47}$$

with

$$A = (d_1 - d_0)(d_1 + d_0)f^{[1]} + (d_2 - d_1)(d_2 + d_1)f^{[2]} - d_2^2 f^{[3]} + 2k\Delta_F^\rho. \tag{48}$$

Given the reservation price r, we can derive the probability distribution over the number of searches: If $k < \bar{k}_1$, we have

$$\Pr(n; k) = F^{[1]}(r)(1 - F^{[1]}(r))^{n-1} \text{ and } \Pr(n = 100; k) = (1 - F^{[1]}(r))^{99}. \tag{49}$$

If $\bar{k}_1 \leq k < \bar{k}_2$, we have

$$\Pr(n; k) = F^{[2]}(r)(1 - F^{[2]}(r))^{n-1} \text{ and } \Pr(n = 100; k) = (1 - F^{[2]}(r))^{99}, \tag{50}$$

and if $\bar{k}_2 \leq k < \bar{k}_3$, we have

$$\Pr(n;k) = F^{[3]}(r)(1 - F^{[3]}(r))^{n-1} \text{ and } \Pr(n = 100;k) = (1 - F^{[3]}(r))^{99}. \tag{51}$$

Derivation of the distribution over purchase prices for given search cost parameter k, uniform price distribution. We derive the distribution over purchase prices. The search cost parameter $k < \bar{k}$ implies the reservation price $r_k < b$, see equation (39). Given that the price distribution is uniform on the interval $[a, b]$, the density over purchase prices equals

$$f(p;k) = \frac{1}{r_k - a} \tag{52}$$

for $p \in [a, r]$ and zero otherwise.

Derivation of the distribution over purchase prices for given search cost parameter k, skewed price distribution. The cost parameter k implies the reservation price r_k as defined in the equations (45), (47), and (48). If $r_k \in [a, d_1)$, the density over purchase prices is given by

$$f(p;k) = \begin{cases} \frac{1}{r_k - d_0} & \text{if } p \in [a, r_k] \\ 0 & \text{else} \end{cases}. \tag{53}$$

If $r_k \in [d_1, d_2)$, it equals

$$f(p;k) = \begin{cases} \frac{f^{[1]}}{F^{[2]}(r_k)} & \text{if } p \in [a, d_1) \\ \frac{f^{[2]}}{F^{[2]}(r_k)} & \text{if } p \in [d_1, r_k] \\ 0 & \text{else} \end{cases} \tag{54}$$

and if $r_k \in [d_2, b]$, it is given by

$$f(p;k) = \begin{cases} \frac{f^{[1]}}{F^{[3]}(r_k)} & \text{if } p \in [a, d_1) \\ \frac{f^{[2]}}{F^{[3]}(r_k)} & \text{if } p \in [d_1, d_2) \\ \frac{f^{[3]}}{F^{[3]}(r_k)} & \text{if } p \in [d_2, r_k] \\ 0 & \text{else} \end{cases}. \tag{55}$$

A.4.2 Computations for the Non-Sequential Search Model

Derivation of the distribution over the number of searches for given search cost parameter k, uniform price distribution. We derive the distribution over the number of searches for the non-sequential search model when the price distribution is uniform on the interval $[a, b]$. From inequality (6) we obtain a cost bound k_n with the following interpretation: If $k > k_n$, the optimal number of searches for the DM is $n - 1$ or lower; if $k \leq k_n$, the optimal number of searches is n or higher. At a uniform price distribution, the expected value of expenses after n searches

$\mathbb{E}(v;n)$ is given by equation (12). With this, we obtain the cost bound

$$k_n = \frac{b-a}{\Delta_F^\rho}\frac{1}{n(n+1)}. \tag{56}$$

The set of cost bounds $k_1, k_2, ...k_{100}$ characterizes the distribution over the number of searches.

Derivation of the distribution over the number of searches for given search cost parameter k, skewed price distribution. We derive the distribution over the number of searches for the non-sequential search model when the price distribution is skewed. As for the case of a uniform price distribution, we derive cost bounds k_n. With a skewed price distribution, the expected value of expenses after n searches $\mathbb{E}(v;n)$ is given by equation (31). With this, we obtain the cost bound

$$\begin{aligned} k_n &= \frac{1}{\Delta_F^\rho}\left[\frac{1}{f^{[1]}}\frac{1}{n}[1-(1-(d_1-a)f^{[1]})^n] - \frac{1}{f^{[1]}}\frac{1}{n+1}[1-(1-(d_1-a)f^{[1]})^{n+1}]\right. \\ &\quad + \frac{1}{f^{[2]}}\frac{1}{n}\left[(1-(d_1-a)f^{[1]})^n - (1-(d_1-a)f^{[1]}-(d_2-d_1)f^{[2]})^n\right] \\ &\quad - \frac{1}{f^{[2]}}\frac{1}{n+1}\left[(1-(d_1-a)f^{[1]})^{n+1} - (1-(d_1-a)f^{[1]}-(d_2-d_1)f^{[2]})^{n+1}\right] \\ &\quad + \frac{1}{f^{[2]}}\frac{1}{n}\left[1-(d_1-a)f^{[1]}-(d_2-d_1)f^{[2]}\right]^n \\ &\quad \left. - \frac{1}{f^{[2]}}\frac{1}{n+1}\left[1-(d_1-a)f^{[1]}-(d_2-d_1)f^{[2]}\right]^{n+1}\right]. \end{aligned} \tag{57}$$

These set of cost bound $k_1, k_2, ...k_{100}$ then characterizes for each given cost parameter k the distribution over the number of searches.

Derivation of the distribution over purchase prices for given search cost parameter k, uniform price distribution. We derive the distribution over purchase prices for the non-sequential search model when the price distribution is uniform on the interval $[a,b]$. The search cost parameter k implies the number of searches n_k according to the bounds defined in (56). For a given price distribution F, the distribution over purchase prices after n_k searches is given by

$$F(p;n_k) = 1-(1-F(p))^{n_k}. \tag{58}$$

Hence, for the uniform distribution, the density over purchase prices when the search cost parameter equals k is given by

$$f(p;k) = \frac{n_k}{b-a}\left(\frac{b-p}{b-a}\right)^{n_k-1}. \tag{59}$$

for $p \in [a,b]$ and zero otherwise.

Derivation of the distribution over purchase prices for given search cost parameter k, skewed price distribution. The search cost parameter k implies the number of searches n_k according to the bounds defined in (57). The density over the purchase price when the search cost parameter equals k is given by

$$f(p;k) = \begin{cases} n_k f^{[1]}(1 - F^{[1]}(p))^{n_k - 1} & \text{if } p \in [a, d_1) \\ n_k f^{[2]}(1 - F^{[2]}(p))^{n_k - 1} & \text{if } p \in [d_1, d_2) \\ n_k f^{[3]}(1 - F^{[3]}(p))^{n_k - 1} & \text{if } p \in [d_2, b] \\ 0 & \text{else} \end{cases}. \quad (60)$$

A.5 Instructions and Screenshots

This appendix shows the instructions to the baseline treatment $S1.0$.

Instructions Shopping Task Part 1/5

The next part of the study is about buying a fictitious product at the lowest possible price. We call it "Product A".

Your budget for Product A is $6.00. Your earnings from this part of the study increase in the price savings that you realize. That is, if you buy Product A at price *P*, then your earnings will be *$6.00-P*.

The lower the price at which you purchase Product A, the higher will be your earnings.

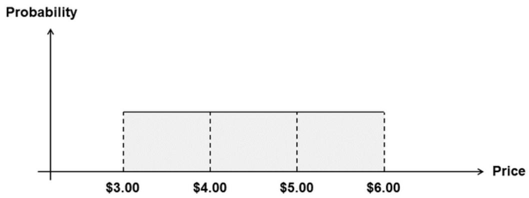
The earnings from this part of the study will be paid as a bonus in MTurk (additional to the $1 participation fee).

You can search for the lowest price for product A in up to 100 online shops. On the next page we will explain how this works.

Next

Instructions Shopping Task Part 2/5

You will get access to up to 100 online shops that offer Product A. The price of each online shop ranges from $3.00 to $6.00. The following graph shows how likely it is that the price of a shop is in a certain range.



Therefore:

- Prices range from $3.00 to $6.00.
- All prices are equally probable.

You do not have to search immediately. You can do this anytime within the next 3 days. You can also continue your search after a break. You can use the link to this study to access the online shopping task anytime.

Back

Next

Instructions Shopping Task Part 3/5

To find out the price of an online shop, a 16-digit code must be entered. This code will be given to you as soon as you click on the "Show Code" button. It needs to be entered into an input field, which appears as soon as you click on the "Show Input Field" button.

Note that the code cannot be entered by copy and paste. Thus, you have to record it somehow (for example by writing it down). After entering the code, the price will be displayed.

Example Shop:

To illustrate this procedure, please search the shop below. Once you successfully searched the shop click on the "Next" button to proceed.

Show Code

Back

Instructions Shopping Task Part 4/5

Once you learn the price of Product A at an online shop, it appears on a list of the prices that you have already seen.

You can then buy the product by clicking on the price of an online shop on this list **or** you can continue searching for the lowest price.

As soon as you purchase Product A, you will reach the final page with the completion code to copy in your HIT.

If you do not want to search for the lowest price at all, you can press the red "I do not want to search" button (your bonus then will be zero).

If you visit some online shops but do not buy Product A from any of them, we cannot pay you a bonus.

Back Next

Instructions Shopping Task Part 5/5

Bonus Payment:

Your bonus from this part of the study is determined by the price savings you realize:

If you buy Product A at price P in one of the online shops, we pay you a bonus of $6.00 - P.

Payment Scheme:

Your Bonus Payment = $6.00 - Price at which you buy Product A

Comprehension Question:

To make sure you understand the payment structure, please answer the following question:

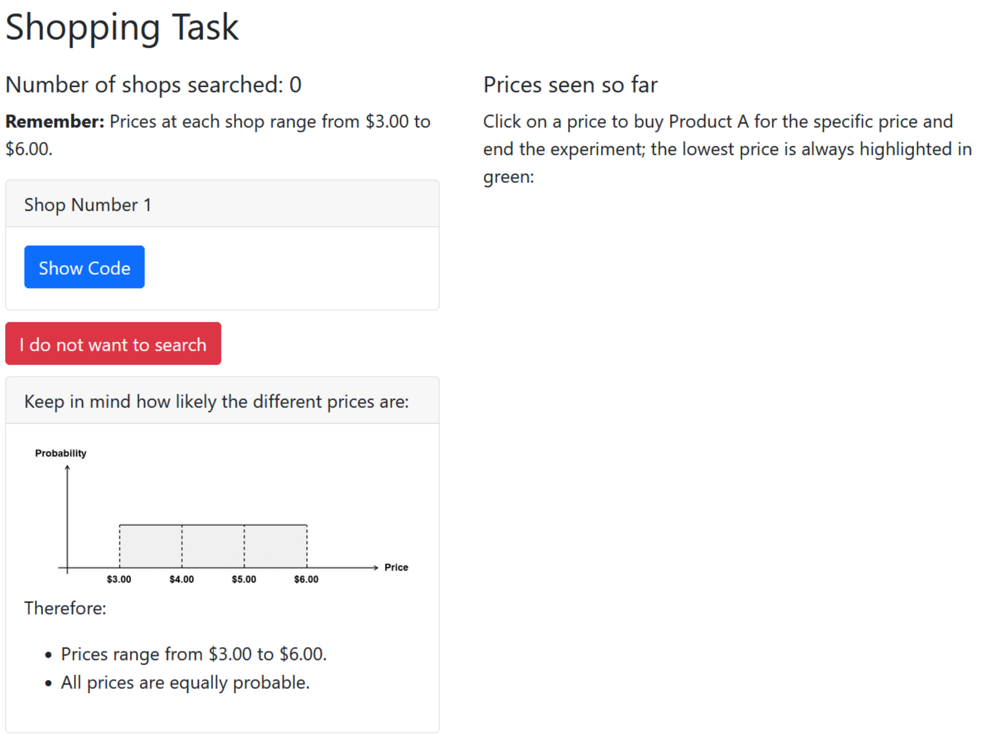
Suppose that after searching 2 times for the lowest price, a shopper buys Product A for $4.20. What will be the shopper's bonus?

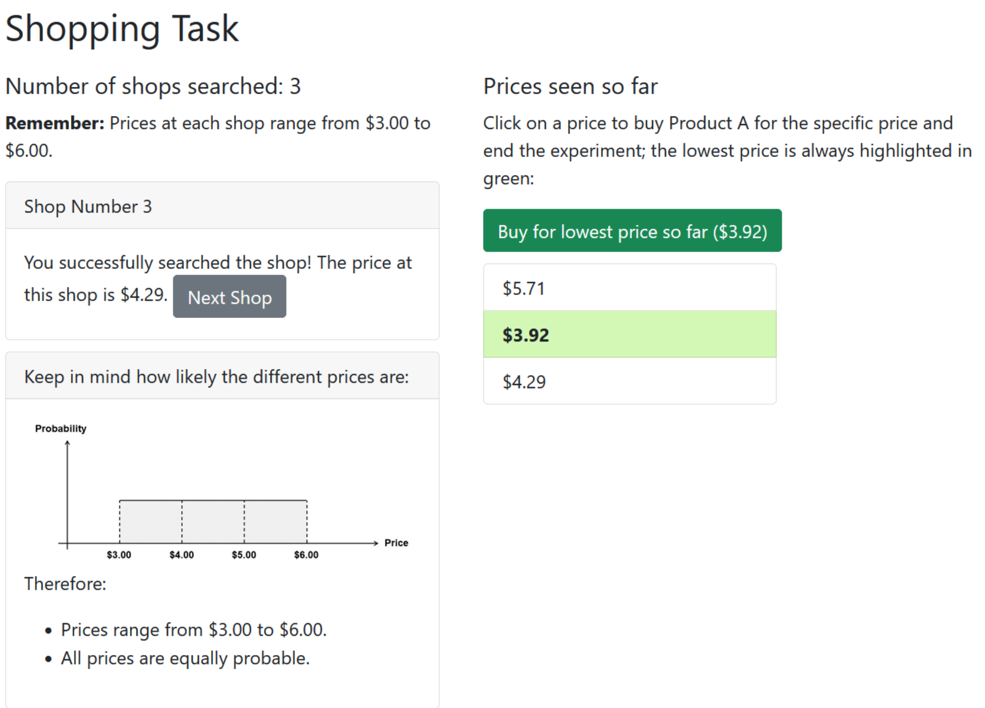
Open this select menu

Submit

Back

These two figures show the screen of the search task in the baseline treatment after zero and three searches, respectively.





A.6 Balancing Tables

Table A1: Balancing Tables: Demographic Variables and Labor Supply

Sample, Treatment	N	Share Females	Age	Average hourly Earnings	Average hours per Week
AMT $S0.2-pr4$	216	0.407	34.55 (10.04)	11.71 (12.74)	34.60 (18.08)
AMT $S0.2-pr8$	202	0.396	34.99 (9.81)	13.44 (14.20)	33.38 (18.57)
AMT $S0.2-pr12$	194	0.418	35.37 (10.64)	12.57 (13.08)	35.35 (18.03)
AMT $S5.0$	190	0.416	34.57 (10.34)	11.94 (12.88)	35.26 (22.54)
AMT $S1.0$	213	0.441	34.88 (10.09)	12.62 (14.10)	35.90 (18.29)
AMT $S1.0-$ noinfo	210	0.419	35.66 (10.32)	11.41 (13.40)	34.49 (20.62)
ANOVA p-value		0.9654	0.8587	0.6821	0.8331
AMT $S1.0-l$	202	0.431	33.42 (8.75)	11.17 (12.70)	38.00 (22.75)
AMT $S1.0-l$.noinfo	192	0.385	34.31 (9.33)	11.41 (13.28)	38.01 (21.06)
AMT $S1.0-r$	199	0.342	34.89 (9.59)	11.29 (14.02)	39.88 (25.53)
AMT $S1.0-r$.noinfo	209	0.340	35.04 (9.39)	10.76 (13.39)	38.24 (21.48)
ANOVA p-value		0.1863	0.2791	0.9648	0.8139
PRO $S1.0-l$	115	0.591	39.84 (13.63)	8.57 (4.65)	11.00 (8.74)
PRO $S1.0-l$.noinfo	134	0.530	38.90 (12.12)	8.77 (5.97)	10.82 (8.52)
PRO $S1.0-r$	152	0.605	37.55 (12.24)	8.14 (3.90)	11.33 (8.27)
PRO $S1.0-r$.noinfo	161	0.590	39.43 (12.55)	7.62 (4.06)	10.98 (8.82)
ANOVA p-value		0.5934	0.4436	0.1581	0.9657

Notes: Standard deviation in parentheses. Age in years, average hourly earnings in USD.

Table A2: Balancing Tables: Personal Characteristics

Sample, Treatment	N	Education Score	CRT Score	Willingness to take risks	Trust
AMT $S\,0.2 - pr4$	216	3.03 (0.58)	1.26 (0.94)	7.82 (1.89)	7.84 (1.98)
AMT $S\,0.2 - pr8$	202	3.14 (0.55)	1.46 (0.99)	7.65 (2.15)	7.75 (1.93)
AMT $S\,0.2 - pr12$	194	3.10 (0.59)	1.25 (0.95)	7.68 (2.10)	7.86 (1.93)
AMT $S\,5.0$	190	3.12 (0.60)	1.36 (0.97)	7.54 (2.01)	7.62 (1.91)
AMT $S\,1.0$	213	3.15 (0.60)	1.30 (0.99)	7.61 (2.12)	7.68 (2.01)
AMT $S\,1.0$ − noinfo	210	3.13 (0.63)	1.50 (0.94)	7.71 (1.88)	7.65 (1.87)
ANOVA p-value		0.3083	0.0362	0.7929	0.7374
AMT $S\,1.0 - l$	202	3.14 (0.58)	1.51 (1.04)	7.80 (1.91)	7.87 (1.83)
AMT $S\,1.0 - l$.noinfo	192	3.08 (0.58)	1.40 (1.03)	7.86 (2.04)	7.68 (1.90)
AMT $S\,1.0 - r$	199	3.22 (0.52)	1.45 (1.09)	7.79 (1.96)	7.80 (1.90)
AMT $S\,1.0 - r$.noinfo	209	3.15 (0.51)	1.55 (1.11)	7.69 (2.30)	7.80 (1.91)
ANOVA p-value		0.1020	0.4978	0.8791	0.8092
PRO $S\,1.0 - l$	115	2.82 (0.78)	1.56 (1.16)	4.66 (2.50)	4.47 (2.33)
PRO $S\,1.0 - l$.noinfo	134	2.72 (0.74)	1.71 (1.16)	5.13 (2.44)	4.41 (2.30)
PRO $S\,1.0 - r$	152	2.86 (0.75)	1.41 (1.11)	4.90 (2.54)	4.47 (2.30)
PRO $S\,1.0 - r$.noinfo	161	2.84 (0.74)	1.50 (1.12)	4.97 (2.55)	4.66 (2.27)
ANOVA p-value		0.4364	0.1578	0.5325	0.8025

Notes: Standard deviation in parentheses. Education is indicated on a scale from 0 to 4 (0 = No degree, 1 = Some high school, 2 = High school degree, 3 = Bachelor's degree, 4 = Master's degree or higher); CRT score is on a scale from 0 to 3 and shows the number of correct answers in the CRT test; willingness to take risk is on a scale from 0 (not willing to take risk at all) to 10 (very willing to take risk); trust is indicates on a scale from 0 (people can't be trusted at all) to 10 (people can be fully trusted).

A.7 Empirical Predictions: Detailed Results

We implement the three tests. Table A3 shows the results on recall (Test 1a and Test 1b) and Table A4 displays the results on the price-dependency of search (Test 2 and Test 3). For Test 1a we find that the share of subjects who purchase from the last sampled shop or search all shops (among those who search at least one shop) varies between 34.1 and 70.3 percent. Thus, there is a substantial share of subjects who recall previously searched shops in all treatments, which is inconsistent with sequential search and constant marginal search costs. In the Prolific samples, the share of subjects who recall is significantly larger in the no-information treatment than in the information treatments. However, this is not the case in the AMT samples.

To implement Test 1b, we consider only those subjects who search at least two, but not all shops. For subjects who non-sequentially search n shops, the probability of trade with the last sampled shop is $\frac{1}{n}$. From this, we derive the predicted average probability of trading with the last sampled shop and we compare this value to the actual share of subjects who traded with the last sampled shop. Next, to implement Test 2, we compare the average price observed in the first shop between subjects who only search once and subjects who search multiple times. Under sequential search and search without priors, the average price observed in the first shop should be larger for subjects who search multiple times; under non-sequential search this average price should be the same for both groups. Finally, to implement Test 3, we derive through a linear regression on all individual searches by how much the probability of continued search increases if the price increases by one USD at the current shop. Under sequential search and search without priors, there should be a positive association between the price at the current shop and the probability of continued search; under non-sequential search, there should be no such association.

Taking Test 1b, Test 2, and Test 3 together (and ignoring recall) generates the following result: Search is consistent with sequential search (and search without priors) and inconsistent with non-sequential search in the treatments AMT $S1.0$, AMT $S1.0-$noinfo , PRO $S1.0-l$, and PRO $S1.0-r$. In contrast, search is consistent with non-sequential search and inconsistent with sequential search (and search without priors) in the treatments AMT $S1.0-r$, AMT $S1.0-r$.noinfo, and PRO $S1.0-l$.noinfo. For each of the remaining treatments there is at least one test that rejects sequential search (and search without priors) as well as one test that rejects non-sequential search. There do not seem to be robust, systematic differences between treatments with and without information about the price distribution. Overall, we conclude that none of the three search models is fully consistent with subjects' search behavior.

Table A3: Sequential versus Non-Sequential Search – Recall

Test 1a (Recall I)	*N*	Share purchase last sampled shop or search all shops	difference *p*-value
AMT S 1.0	207	0.599	0.340
AMT S 1.0 – noinfo	201	0.552	
AMT S 1.0 – *l*	198	0.444	0.273
AMT S 1.0 – *l*.noinfo	192	0.500	
AMT S 1.0 – *r*	194	0.479	0.946
AMT S 1.0 – *r*.noinfo	208	0.476	
PRO S 1.0 – *l*	106	0.557	0.001
PRO S 1.0 – *l*.noinfo	123	0.341	
PRO S 1.0 – *r*	145	0.703	0.000
PRO S 1.0 – *r*.noinfo	155	0.439	
Test 1b (Recall II)	*N*	predicted vs. actual av. share purchase last sampled shop	difference *p*-value
AMT S 1.0	115	0.201 vs. 0.278	0.063
AMT S 1.0 – noinfo	124	0.184 vs. 0.274	0.008
AMT S 1.0 – *l*	134	0.132 vs. 0.179	0.143
AMT S 1.0 – *l*.noinfo	119	0.121 vs. 0.193	0.041
AMT S 1.0 – *r*	122	0.158 vs. 0.172	0.635
AMT S 1.0 – *r*.noinfo	133	0.169 vs. 0.180	0.679
PRO S 1.0 – *l*	90	0.205 vs. 0.478	0.000
PRO S 1.0 – *l*.noinfo	105	0.176 vs. 0.229	0.165
PRO S 1.0 – *r*	81	0.287 vs. 0.469	0.001
PRO S 1.0 – *r*.noinfo	114	0.198 vs. 0.237	0.307

Notes: Test 1a – For each treatment we indicate the share of subjects who purchase from the last sampled shop or who search all shops among those subjects who search at least one shop; *p*-values from two-sided t-tests which compare these shares between a treatment with information about the price distribution and the corresponding no-information treatment. Test 1b – Among all searchers who search at least two but not all shops we compare the (according to the non-sequential search paradigm) predicted share and the actual share of subjects who purchase from the last sampled shop; *p*-values from χ^2 tests.

Table A4: Sequential versus Non-Sequential Search – Price-Dependence

Test 2 (Price-Dependence I)	*N*	one search vs. multiple searches	difference *p*-value
AMT S 1.0	207	4.25 vs. 4.52	0.037
AMT S 1.0 – noinfo	201	4.28 vs. 4.61	0.014
AMT S 1.0 – l	198	5.01 vs. 5.09	0.503
AMT S 1.0 – l.noinfo	192	5.06 vs. 5.21	0.140
AMT S 1.0 – r	194	3.75 vs. 3.77	0.896
AMT S 1.0 – r.noinfo	208	3.80 vs. 3.91	0.219
PRO S 1.0 – l	106	4.56 vs. 5.19	0.001
PRO S 1.0 – l.noinfo	123	5.10 vs. 5.15	0.778
PRO S 1.0 – r	145	3.69 vs. 3.99	0.003
PRO S 1.0 – r.noinfo	155	3.60 vs. 3.89	0.007
Test 3 (Price-Dependence II)	*N*	change in prob. of continued search	*p*-value
AMT S 1.0	2235	2.10 %	0.008
AMT S 1.0 – noinfo	2622	1.50 %	0.020
AMT S 1.0 – l	4154	1.48 %	0.018
AMT S 1.0 – l.noinfo	3845	1.01 %	0.125
AMT S 1.0 – r	2743	-0.93 %	0.269
AMT S 1.0 – r.noinfo	2863	1.01 %	0.172
PRO S 1.0 – l	730	14.82 %	0.000
PRO S 1.0 – l.noinfo	1102	1.29 %	0.384
PRO S 1.0 – r	452	14.50 %	0.000
PRO S 1.0 – r.noinfo	1054	3.32 %	0.038

Notes: Test 2 – Among all individuals who search at least one shop we compare the average price at the first shop observed by subjects who search exactly one shop and subjects who search more than one shop; *p*-values from two-sided t-tests. Test 3 – For all individual price observations we derive the average probability of continued search when the price at the current shop increases by one USD; *p*-values from OLS regressions; standard errors are clustered at the subject level.

A.8 Direct Search Costs

We briefly compare the search cost estimates from the two models to subjects' *direct search costs*. For each individual, we record the earnings for one hour of activity (on AMT or Prolific) as well as the average time she needs to obtain a price quote. An individual's direct search costs are defined as

$$\text{direct search costs} = \text{average hourly earnings} \times \frac{\text{mean search duration in seconds}}{3600}. \quad (61)$$

The average direct search costs are 0.25 USD (sd = 0.59) in the November 2023 AMT sample, 0.18 USD (sd = 0.25) in the June 2024 AMT sample, and 0.14 USD (sd = 0.15) in the June 2024 PRO sample. In Table A5 below we compare, for each information and no-information treatment, the search cost estimates to direct search costs. Overall, direct search costs are roughly in line with estimated search costs. They would differ by a factor of around five or more if we would not take context effects into account.

Table A5: Estimated Mean Search Costs and Direct Search Costs

Sample Treatment	Estimated Search Costs (sequential)	Estimated Search Costs (non-sequential)	Direct Search Costs
AMT S 1.0	0.185 (0.310)	0.219 (0.334)	0.228 (0.298)
AMT S 1.0 – noinfo	0.169 (0.298)	0.192 (0.316)	0.207 (0.312)
AMT S 1.0 – l	0.130 (0.298)	0.141 (0.314)	0.191 (0.273)
AMT S 1.0 – l.noinfo	0.136 (0.306)	0.153 (0.327)	0.187 (0.223)
AMT S 1.0 – r	0.100 (0.258)	0.129 (0.299)	0.197 (0.292)
AMT S 1.0 – r.noinfo	0.101 (0.259)	0.123 (0.292)	0.163 (0.198)
PRO S 1.0 – l	0.149 (0.285)	0.138 (0.257)	0.148 (0.126)
PRO S 1.0 – l.noinfo	0.127 (0.258)	0.120 (0.233)	0.154 (0.198)
PRO S 1.0 – r	0.184 (0.322)	0.202 (0.324)	0.144 (0.129)
PRO S 1.0 – r.noinfo	0.067 (0.172)	0.081 (0.180)	0.123 (0.128)

Notes: Standard errors in parentheses. The search cost estimates for each model originate from the regressions in Table 3 and Table 4, respectively. The last column shows the average direct search costs.

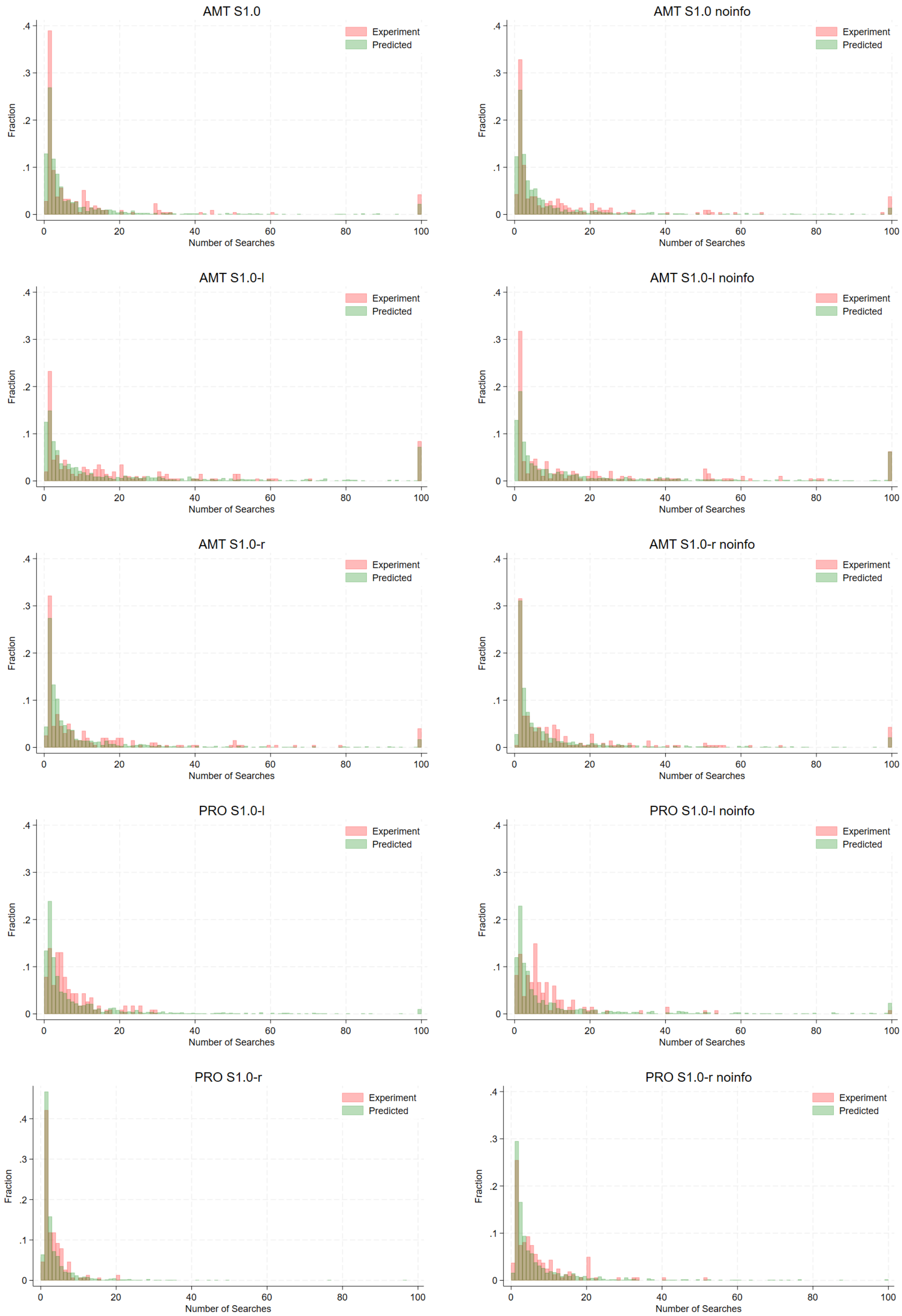


Figure A1: Sequential Search – Observed vs. predicted number of searches

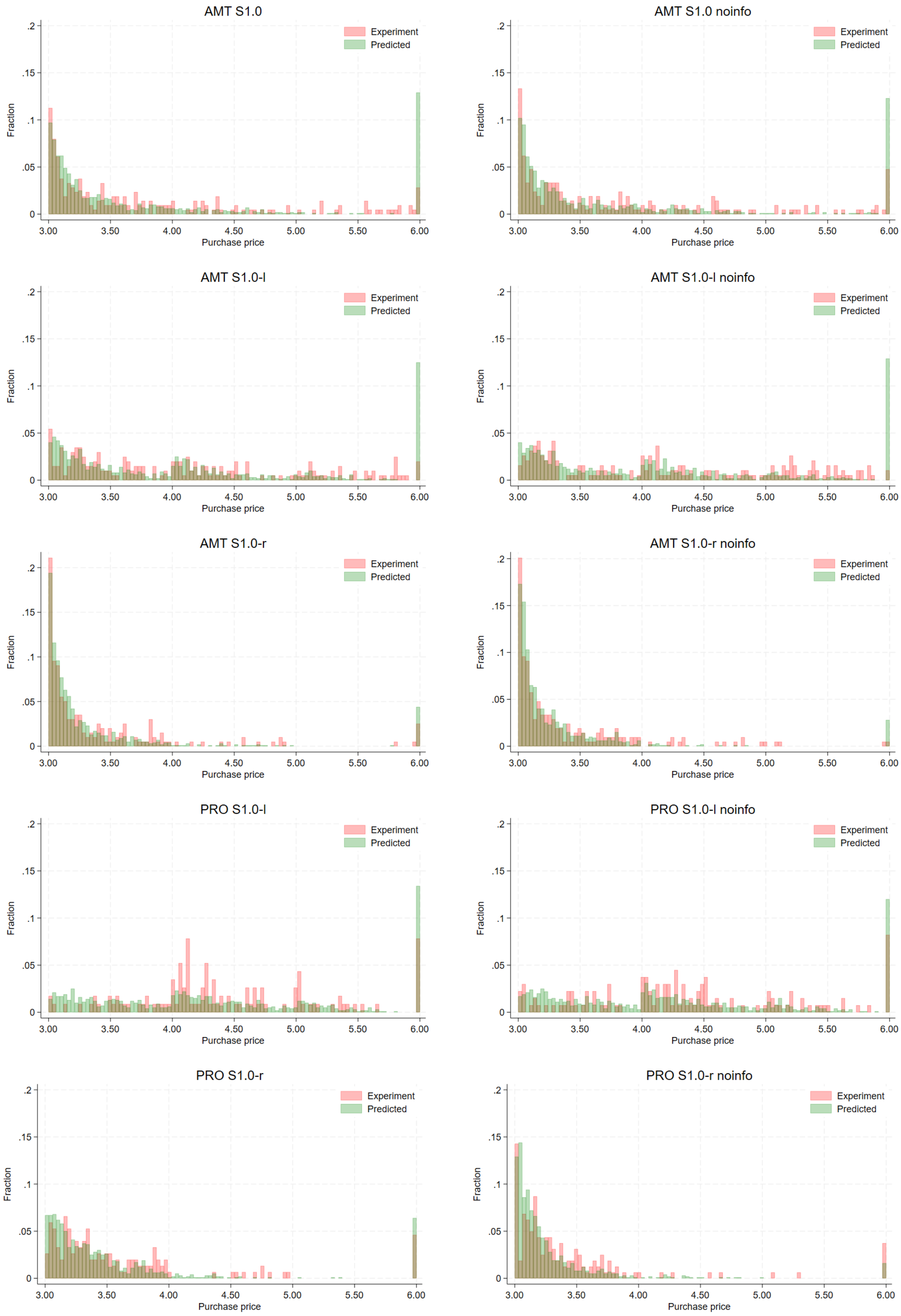


Figure A2: Sequential Search – Observed vs. predicted purchase prices

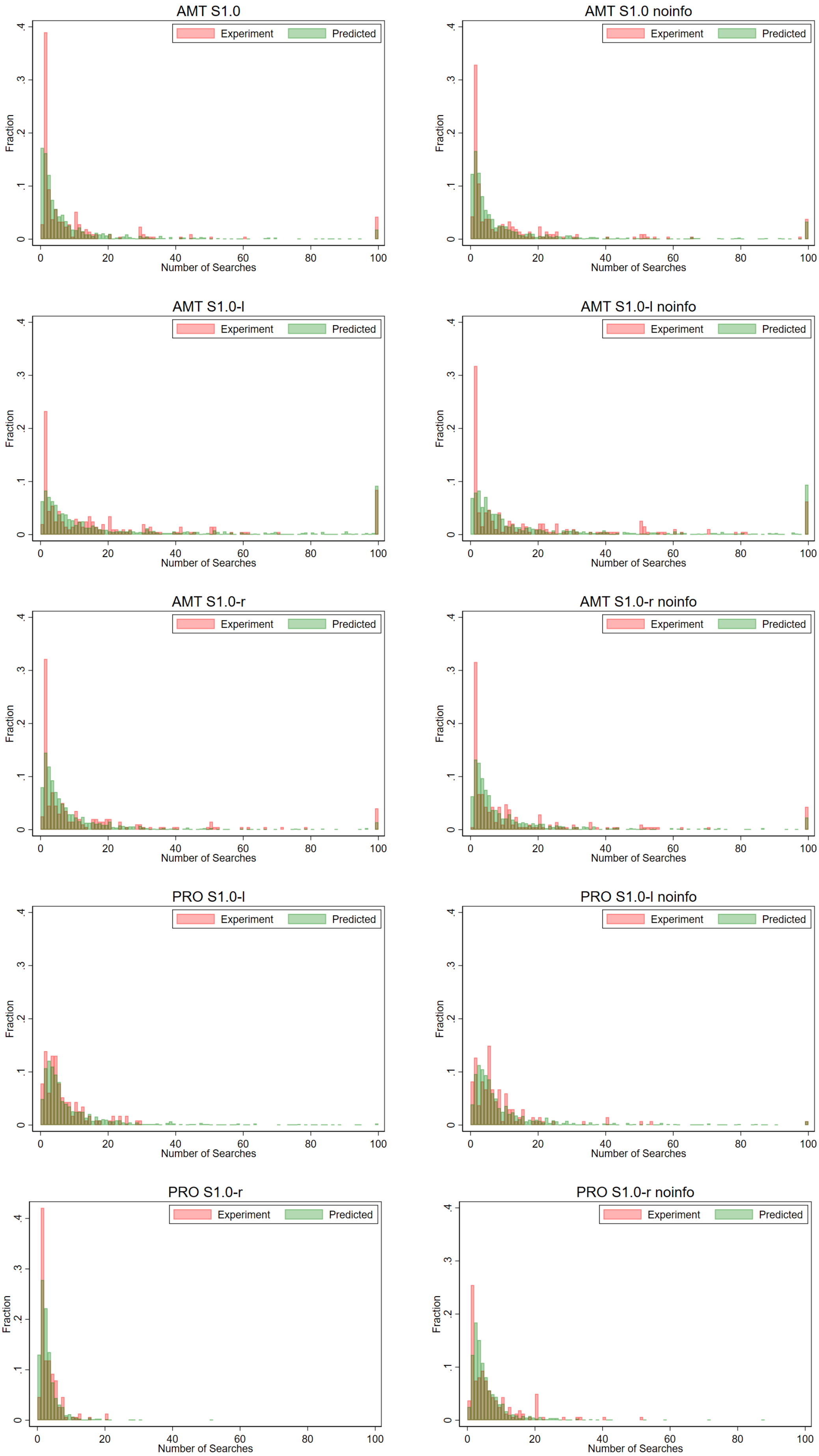


Figure A3: Non-sequential Search – Observed vs. predicted distributions number of searches

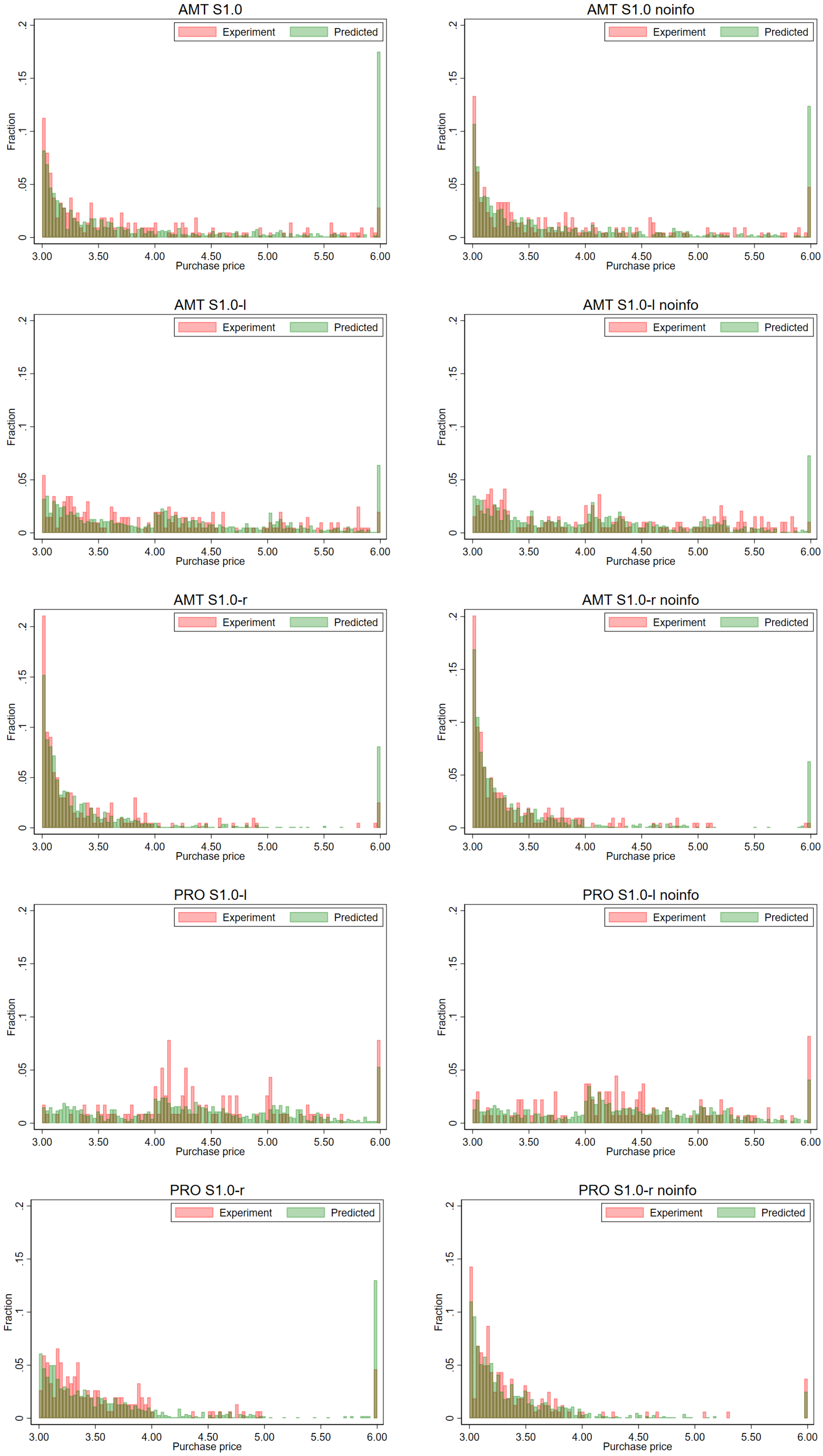


Figure A4: Non-sequential Search – Observed vs. predicted purchase prices

B Online Appendix

Online Appendix B.1 contains the tables for the evaluation of search cost estimates. These generate the numbers in Table 5. Online Appendix B.2 introduces the search without priors model and shows the search cost estimates as well as the evaluation tables for this model. Finally, Online Appendix B.3 shows all results for the variable *restricted number of searches*.

B.1 Tables from Evaluation

Table B1: Observed vs. Predicted Number of Searches (Sequential Search)

$G^{[1]}$ / $\hat{G}^{[1]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**1.48**	3.21	6.82	3.97	7.35	6.81	8.73	8.11	3.53	0.31
	(1.56)	(1.64)	(2.14)	(2.18)	(1.68)	(1.64)	(1.03)	(1.36)	(0.55)	(0.79)
	0.00	1.00	8.00	4.50	2.00	3.00	1.00	2.00	0.00	2.00
	0.30	0.28	0.39	0.44	0.30	0.29	0.42	0.41	0.27	0.30
	0.24	0.24	0.52	0.54	0.30	0.27	0.53	0.56	0.19	0.35
AMT $S1.0$ noinfo	0.18	**3.66**	2.50	3.96	6.73	7.13	11.87	8.60	4.68	0.83
	(1.60)	**(1.62)**	(2.19)	(2.19)	(1.68)	(1.62)	(1.14)	(1.37)	(0.56)	(0.78)
	0.00	**1.00**	7.00	4.50	2.00	3.00	1.00	2.00	0.00	2.00
	0.31	**0.28**	0.38	0.45	0.28	0.30	0.43	0.41	0.29	0.29
	0.27	**0.25**	0.44	0.55	0.22	0.30	0.53	0.56	0.20	0.26
AMT $S1.0-l$	0.22	2.79	**1.05**	1.75	6.01	5.64	13.19	10.70	4.20	1.22
	(1.57)	(1.62)	**(2.19)**	(2.19)	(1.69)	(1.64)	(1.11)	(1.37)	(0.51)	(0.78)
	1.00	1.00	**4.00**	3.50	2.00	3.00	1.00	0.00	0.00	2.00
	0.32	0.26	**0.36**	0.41	0.28	0.29	0.42	0.42	0.30	0.28
	0.30	0.15	**0.41**	0.44	0.20	0.29	0.46	0.54	0.21	0.26
AMT $S1.0-l$ noinfo	1.64	2.17	2.29	**1.80**	5.80	4.97	12.50	10.24	4.24	1.70
	(1.53)	(1.63)	(2.18)	**(2.19)**	(1.70)	(1.67)	(1.09)	(1.37)	(0.53)	(0.80)
	1.00	0.00	5.00	**2.50**	2.00	3.00	1.00	0.00	0.00	2.00
	0.31	0.28	0.34	**0.41**	0.28	0.29	0.43	0.41	0.29	0.30
	0.29	0.24	0.34	**0.45**	0.26	0.30	0.49	0.54	0.21	0.29
AMT $S1.0-r$	3.87	0.58	2.51	2.25	**3.78**	3.13	17.19	14.73	6.37	3.45
	(1.62)	(1.66)	(2.22)	(2.23)	**(1.72)**	(1.68)	(1.18)	(1.45)	(0.61)	(0.85)
	3.00	1.00	2.00	1.50	**1.00**	2.00	3.00	2.00	1.00	1.00
	0.35	0.31	0.33	0.42	**0.30**	0.27	0.45	0.44	0.34	0.29
	0.34	0.29	0.33	0.51	**0.25**	0.25	0.54	0.57	0.27	0.23
AMT $S1.0-r$ noinfo	2.89	1.39	2.46	2.94	4.25	**3.56**	17.36	16.00	5.85	1.64
	(1.60)	(1.69)	(2.23)	(2.23)	(1.70)	**(1.67)**	(1.20)	(1.45)	(0.59)	(0.79)
	2.00	2.00	4.00	0.50	1.00	**2.00**	3.00	3.00	1.00	1.00
	0.34	0.30	0.35	0.40	0.29	**0.27**	0.45	0.46	0.32	0.29
	0.33	0.25	0.39	0.45	0.24	**0.23**	0.51	0.64	0.24	0.25
PRO $S1.0-l$	4.92	7.16	10.47	9.81	10.63	9.98	**2.43**	2.21	0.66	2.74
	(1.48)	(1.55)	(2.08)	(2.09)	(1.62)	(1.58)	**(0.79)**	(1.19)	(0.34)	(0.65)
	0.00	1.00	7.00	4.50	3.00	3.00	**1.00**	2.00	0.00	2.00
	0.26	0.27	0.35	0.41	0.26	0.29	**0.33**	0.39	0.20	0.28
	0.17	0.32	0.38	0.49	0.19	0.30	**0.33**	0.52	0.10	0.34
PRO $S1.0-l$ noinfo	5.02	6.48	10.63	8.35	9.68	9.98	4.60	**3.26**	1.03	2.59
	(1.48)	(1.56)	(2.07)	(2.11)	(1.63)	(1.57)	(0.88)	**(1.22)**	(0.33)	(0.65)
	0.00	0.00	7.00	3.50	2.00	3.00	1.00	**2.00**	0.00	2.00
	0.28	0.26	0.33	0.39	0.26	0.24	0.34	**0.37**	0.22	0.28
	0.34	0.22	0.37	0.42	0.18	0.12	0.34	**0.46**	0.12	0.38
PRO $S1.0-r$	5.96	8.51	13.17	11.71	10.75	10.28	0.99	1.41	**0.46**	3.63
	(1.47)	(1.54)	(2.04)	(2.07)	(1.62)	(1.58)	(0.77)	(1.11)	**(0.33)**	(0.63)
	0.00	1.00	8.00	5.50	3.00	4.00	2.00	3.00	**1.00**	3.00
	0.29	0.24	0.38	0.44	0.26	0.28	0.32	0.38	**0.22**	0.30
	0.33	0.15	0.53	0.56	0.16	0.23	0.34	0.52	**0.14**	0.41
PRO $S1.0-r$ noinfo	1.65	4.46	4.73	3.30	7.58	7.21	10.74	8.15	3.07	**0.30**
	(1.52)	(1.58)	(2.13)	(2.15)	(1.66)	(1.60)	(1.00)	(1.27)	(0.42)	**(0.71)**
	2.00	1.00	5.00	1.50	1.00	2.00	2.00	1.00	0.00	**1.00**
	0.32	0.28	0.32	0.38	0.30	0.28	0.38	0.39	0.29	**0.28**
	0.30	0.24	0.34	0.44	0.34	0.31	0.36	0.44	0.22	**0.26**

Notes: Differences between predicted and realized distribution over the number of searches when the search model is sequential search. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

Table B2: Observed vs. Predicted Purchase Prices (Sequential Search)

$G^{[2]}$ $\hat{G}^{[2]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**0.00 (0.07) 0.10 0.30 0.22**	0.00 (0.07) 0.06 0.29 0.25	0.32 (0.07) 0.29 0.38 0.41	0.14 (0.07) 0.05 0.43 0.52	0.16 (0.05) 0.10 0.28 0.18	0.18 (0.04) 0.06 0.25 0.15	0.08 (0.08) 0.13 0.51 0.78	0.05 (0.08) 0.17 0.46 0.68	0.06 (0.06) 0.13 0.30 0.28	0.11 (0.06) 0.02 0.27 0.21
AMT $S1.0$ noinfo	0.04 (0.07) 0.11 0.30 0.19	**0.02 (0.07) 0.09 0.30 0.26**	0.21 (0.07) 0.13 0.38 0.42	0.14 (0.07) 0.08 0.45 0.62	0.09 (0.05) 0.05 0.25 0.18	0.12 (0.04) 0.03 0.24 0.13	0.09 (0.08) 0.15 0.50 0.76	0.07 (0.08) 0.17 0.46 0.62	0.12 (0.06) 0.18 0.33 0.37	0.05 (0.05) 0.04 0.26 0.18
AMT $S1.0-l$	0.23 (0.06) 0.19 0.27 0.16	0.24 (0.07) 0.16 0.26 0.14	**0.00 (0.07) 0.08 0.36 0.43**	0.08 (0.07) 0.15 0.41 0.50	0.01 (0.05) 0.01 0.24 0.15	0.04 (0.04) 0.01 0.23 0.14	0.35 (0.08) 0.37 0.53 0.84	0.25 (0.08) 0.40 0.45 0.60	0.20 (0.06) 0.22 0.34 0.40	0.01 (0.05) 0.08 0.25 0.21
AMT $S1.0-l$ noinfo	0.14 (0.07) 0.14 0.30 0.27	0.19 (0.07) 0.15 0.27 0.20	0.03 (0.07) 0.02 0.35 0.31	**0.06 (0.07) 0.10 0.42 0.53**	0.05 (0.05) 0.01 0.22 0.10	0.07 (0.04) 0.00 0.22 0.10	0.36 (0.08) 0.48 0.53 0.81	0.26 (0.08) 0.28 0.46 0.60	0.17 (0.06) 0.20 0.32 0.30	0.04 (0.05) 0.08 0.25 0.19
AMT $S1.0-r$	0.33 (0.06) 0.23 0.26 0.11	0.31 (0.07) 0.20 0.29 0.25	0.15 (0.07) 0.34 0.34 0.35	0.18 (0.07) 0.41 0.38 0.42	**0.06 (0.05) 0.01 0.24 0.16**	0.07 (0.04) 0.03 0.20 0.11	0.49 (0.07) 0.71 0.54 0.83	0.42 (0.08) 0.67 0.48 0.66	0.27 (0.06) 0.24 0.36 0.48	0.11 (0.05) 0.11 0.27 0.25
AMT $S1.0-r$ noinfo	0.27 (0.06) 0.21 0.27 0.15	0.30 (0.07) 0.21 0.28 0.21	0.12 (0.07) 0.25 0.34 0.30	0.25 (0.07) 0.47 0.39 0.44	0.11 (0.05) 0.02 0.25 0.17	**0.07 (0.04) 0.04 0.20 0.11**	0.50 (0.07) 0.70 0.54 0.84	0.46 (0.08) 0.72 0.50 0.74	0.27 (0.06) 0.24 0.35 0.46	0.10 (0.05) 0.11 0.25 0.22
PRO $S1.0-l$	0.09 (0.07) 0.06 0.31 0.22	0.12 (0.07) 0.04 0.29 0.24	0.27 (0.07) 0.26 0.38 0.42	0.15 (0.07) 0.12 0.42 0.53	0.08 (0.05) 0.13 0.31 0.30	0.06 (0.04) 0.09 0.25 0.17	**0.10 (0.07) 0.10 0.46 0.60**	0.01 (0.08) 0.08 0.43 0.53	0.12 (0.06) 0.12 0.28 0.23	0.03 (0.05) 0.00 0.21 0.12
PRO $S1.0-l$ noinfo	0.12 (0.06) 0.06 0.30 0.22	0.15 (0.07) 0.06 0.29 0.23	0.22 (0.07) 0.25 0.39 0.48	0.05 (0.07) 0.06 0.41 0.50	0.03 (0.05) 0.08 0.29 0.25	0.05 (0.04) 0.07 0.25 0.19	0.15 (0.07) 0.14 0.46 0.57	**0.12 (0.08) 0.17 0.42 0.49**	0.20 (0.06) 0.14 0.28 0.24	0.02 (0.05) 0.01 0.23 0.15
PRO $S1.0-r$	0.02 (0.07) 0.04 0.32 0.24	0.02 (0.07) 0.06 0.31 0.27	0.42 (0.07) 0.38 0.42 0.61	0.31 (0.07) 0.23 0.44 0.58	0.10 (0.05) 0.13 0.31 0.28	0.13 (0.04) 0.12 0.30 0.31	0.08 (0.07) 0.01 0.46 0.62	0.12 (0.08) 0.04 0.43 0.55	**0.08 (0.06) 0.08 0.29 0.24**	0.12 (0.05) 0.04 0.25 0.18
PRO $S1.0-r$ noinfo	0.34 (0.06) 0.19 0.29 0.20	0.37 (0.06) 0.16 0.29 0.19	0.10 (0.07) 0.04 0.33 0.31	0.26 (0.07) 0.33 0.38 0.38	0.14 (0.05) 0.01 0.23 0.14	0.12 (0.04) 0.03 0.20 0.11	0.48 (0.07) 0.48 0.51 0.73	0.45 (0.08) 0.47 0.46 0.62	0.34 (0.06) 0.22 0.33 0.42	**0.17 (0.05) 0.10 0.25 0.19**

Notes: Differences between predicted and realized distribution over purchase prices when the search model is sequential search. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

Table B3: Observed vs. Predicted Number of Searches (Non-Sequential Search)

$G^{[1]}$ $\hat{G}^{[1]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**0.72** **(1.56)** **1.00** **0.36** **0.41**	1.74 (1.64) 0.00 0.32 0.31	3.77 (2.17) 6.00 0.34 0.37	3.54 (2.18) 3.50 0.42 0.51	6.75 (1.68) 2.00 0.34 0.36	6.53 (1.62) 3.00 0.37 0.44	11.19 (1.10) 0.00 0.39 0.42	8.85 (1.35) 1.00 0.39 0.46	4.35 (0.53) 0.00 0.35 0.35	0.79 (0.80) 2.00 0.34 0.41
AMT $S1.0$ noinfo	1.77 (1.59) 2.00 0.36 0.38	**0.15** **(1.68)** **1.00** **0.30** **0.29**	1.18 (2.24) 5.00 0.36 0.43	0.85 (2.21) 3.50 0.42 0.53	4.83 (1.71) 1.00 0.32 0.34	4.67 (1.66) 2.00 0.35 0.37	12.76 (1.11) 1.00 0.40 0.43	11.70 (1.40) 0.00 0.41 0.49	6.20 (0.63) 1.00 0.38 0.39	2.50 (0.83) 1.00 0.32 0.35
AMT $S1.0-l$	4.20 (1.61) 4.00 0.40 0.49	2.68 (1.68) 4.00 0.35 0.40	**4.60** **(2.23)** **1.00** **0.36** **0.42**	4.69 (2.24) 1.50 0.45 0.65	3.19 (1.71) 1.00 0.32 0.30	3.77 (1.65) 1.00 0.32 0.34	17.00 (1.15) 4.00 0.43 0.44	17.54 (1.47) 4.00 0.44 0.52	6.94 (0.58) 2.00 0.40 0.43	3.92 (0.82) 0.00 0.32 0.29
AMT $S1.0-l$ noinfo	3.03 (1.58) 4.00 0.41 0.55	0.84 (1.66) 2.00 0.31 0.30	2.67 (2.22) 2.00 0.35 0.39	**3.96** **(2.24)** **0.50** **0.43** **0.60**	3.92 (1.70) 0.00 0.33 0.36	4.51 (1.64) 2.00 0.32 0.32	16.33 (1.16) 4.00 0.42 0.44	14.85 (1.43) 2.00 0.42 0.51	7.25 (0.61) 2.00 0.40 0.45	2.88 (0.80) 0.00 0.29 0.25
AMT $S1.0-r$	4.32 (1.59) 5.00 0.42 0.54	2.56 (1.67) 4.00 0.34 0.38	7.69 (2.26) 1.00 0.38 0.48	8.55 (2.28) 2.50 0.40 0.45	**3.29** **(1.71)** **0.00** **0.32** **0.31**	2.97 (1.66) 1.00 0.33 0.37	21.23 (1.24) 5.50 0.47 0.53	19.03 (1.48) 5.00 0.45 0.57	9.28 (0.66) 3.00 0.44 0.55	4.56 (0.83) 0.00 0.32 0.28
AMT $S1.0-r$ noinfo	5.98 (1.62) 5.00 0.41 0.53	4.08 (1.69) 5.00 0.38 0.45	7.30 (2.26) 0.50 0.36 0.41	8.82 (2.28) 4.50 0.44 0.65	1.09 (1.73) 1.00 0.35 0.37	**1.68** **(1.68)** **0.00** **0.32** **0.35**	21.58 (1.24) 6.00 0.48 0.56	19.82 (1.49) 6.00 0.45 0.55	8.36 (0.63) 2.00 0.42 0.47	6.56 (0.88) 1.00 0.36 0.37
PRO $S1.0-l$	4.93 (1.46) 2.00 0.34 0.47	6.95 (1.54) 1.00 0.29 0.20	10.35 (2.04) 5.00 0.38 0.57	10.39 (2.05) 2.50 0.43 0.65	9.90 (1.62) 1.00 0.30 0.17	9.64 (1.57) 2.00 0.29 0.16	**3.59** **(0.76)** **1.00** **0.28** **0.21**	1.67 (1.12) 0.00 0.32 0.27	0.89 (0.30) 1.00 0.26 0.23	2.51 (0.63) 1.00 0.25 0.25
PRO $S1.0-l$ noinfo	4.41 (1.46) 2.00 0.36 0.49	6.48 (1.54) 1.00 0.28 0.22	9.15 (2.05) 4.00 0.36 0.50	9.14 (2.06) 2.50 0.40 0.48	9.33 (1.63) 1.00 0.30 0.17	9.61 (1.57) 2.00 0.31 0.19	5.43 (0.80) 1.00 0.32 0.27	**2.34** **(1.14)** **0.00** **0.31** **0.27**	1.23 (0.31) 1.00 0.26 0.22	2.18 (0.63) 1.00 0.27 0.31
PRO $S1.0-r$	6.56 (1.45) 1.00 0.29 0.20	8.16 (1.54) 0.00 0.31 0.37	13.44 (2.02) 7.00 0.37 0.59	13.18 (2.03) 4.50 0.40 0.40	11.01 (1.62) 2.00 0.29 0.13	10.79 (1.57) 3.00 0.33 0.27	0.41 (0.69) 0.00 0.26 0.22	1.45 (1.07) 2.00 0.31 0.30	**0.17** **(0.29)** **0.00** **0.22** **0.16**	3.77 (0.62) 2.00 0.30 0.40
PRO $S1.0-r$ noinfo	2.00 (1.48) 4.00 0.38 0.45	4.41 (1.55) 2.00 0.35 0.48	4.96 (2.09) 3.00 0.38 0.53	5.61 (2.09) 0.50 0.43 0.66	8.13 (1.63) 0.00 0.33 0.31	8.17 (1.58) 1.00 0.28 0.15	8.08 (0.85) 4.00 0.36 0.32	6.81 (1.20) 2.00 0.39 0.42	2.77 (0.33) 2.00 0.34 0.36	**0.81** **(0.65)** **0.00** **0.27** **0.27**

Notes: Differences between predicted and realized distribution over the number of searches when the search model is non-sequential search. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

Table B4: Observed vs. Predicted Purchase Prices (Non-Sequential Search)

$G^{[2]}$ $\hat{G}^{[2]}$	AMT S1.0	AMT S1.0 noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT S1.0	**0.31**	0.29	0.36	0.23	0.45	0.50	0.05	0.08	0.27	0.48
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.05)	(0.08)	(0.08)	(0.06)	(0.06)
	0.14	0.17	0.40	0.20	0.20	0.22	0.09	0.03	0.00	0.13
	0.35	0.36	0.38	0.38	0.35	0.36	0.50	0.45	0.35	0.35
	0.36	0.41	0.46	0.42	0.35	0.34	0.71	0.58	0.43	0.36
AMT S1.0 noinfo	0.14	**0.14**	0.30	0.22	0.35	0.39	0.05	0.04	0.18	0.31
	(0.07)	**(0.07)**	(0.07)	(0.07)	(0.06)	(0.05)	(0.08)	(0.08)	(0.06)	(0.06)
	0.00	**0.09**	0.35	0.17	0.13	0.13	0.02	0.09	0.08	0.04
	0.35	**0.32**	0.37	0.38	0.31	0.32	0.49	0.44	0.36	0.31
	0.36	**0.29**	0.45	0.44	0.26	0.28	0.67	0.56	0.46	0.28
AMT $S1.0-l$	0.02	0.08	**0.07**	0.06	0.11	0.21	0.28	0.21	0.00	0.13
	(0.07)	(0.07)	**(0.07)**	(0.07)	(0.05)	(0.05)	(0.07)	(0.08)	(0.06)	(0.06)
	0.11	0.13	**0.13**	0.04	0.07	0.04	0.23	0.22	0.14	0.06
	0.30	0.30	**0.35**	0.38	0.27	0.27	0.50	0.46	0.36	0.28
	0.21	0.28	**0.38**	0.45	0.19	0.22	0.69	0.58	0.47	0.24
AMT $S1.0-l$ noinfo	0.00	0.01	0.15	**0.04**	0.17	0.23	0.19	0.15	0.00	0.14
	(0.07)	(0.07)	(0.07)	**(0.07)**	(0.05)	(0.05)	(0.07)	(0.08)	(0.06)	(0.06)
	0.08	0.08	0.21	**0.02**	0.06	0.09	0.20	0.17	0.15	0.02
	0.32	0.31	0.37	**0.37**	0.30	0.27	0.50	0.44	0.34	0.28
	0.29	0.26	0.42	**0.38**	0.24	0.18	0.66	0.52	0.39	0.23
AMT $S1.0-r$	0.07	0.11	0.00	0.09	**0.14**	0.17	0.35	0.28	0.11	0.09
	(0.07)	(0.07)	(0.07)	(0.07)	**(0.05)**	(0.04)	(0.07)	(0.08)	(0.06)	(0.06)
	0.15	0.13	0.07	0.05	**0.06**	0.04	0.27	0.27	0.21	0.05
	0.32	0.30	0.35	0.37	**0.27**	0.27	0.52	0.46	0.36	0.29
	0.31	0.26	0.41	0.38	**0.19**	0.22	0.76	0.58	0.44	0.26
AMT $S1.0-r$ noinfo	0.08	0.11	0.03	0.09	0.06	**0.12**	0.31	0.31	0.07	0.07
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	**(0.04)**	(0.07)	(0.08)	(0.06)	(0.06)
	0.15	0.16	0.08	0.05	0.02	**0.02**	0.27	0.27	0.18	0.08
	0.31	0.33	0.35	0.39	0.26	**0.24**	0.53	0.46	0.34	0.30
	0.27	0.36	0.39	0.44	0.17	**0.12**	0.78	0.62	0.37	0.28
PRO $S1.0-l$	0.15	0.02	0.31	0.18	0.18	0.23	**0.06**	0.01	0.06	0.20
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.04)	**(0.07)**	(0.08)	(0.06)	(0.06)
	0.14	0.10	0.31	0.21	0.18	0.14	**0.01**	0.03	0.03	0.10
	0.34	0.33	0.40	0.39	0.33	0.30	**0.49**	0.43	0.30	0.30
	0.34	0.35	0.48	0.45	0.30	0.27	**0.66**	0.48	0.29	0.25
PRO $S1.0-l$ noinfo	0.04	0.02	0.25	0.14	0.16	0.19	0.09	**0.03**	0.00	0.13
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.04)	(0.07)	**(0.08)**	(0.06)	(0.05)
	0.06	0.07	0.32	0.18	0.12	0.15	0.05	**0.03**	0.06	0.05
	0.32	0.34	0.39	0.40	0.31	0.28	0.46	**0.44**	0.31	0.26
	0.27	0.37	0.47	0.48	0.26	0.23	0.55	**0.53**	0.28	0.18
PRO $S1.0-r$	0.31	0.24	0.47	0.38	0.38	0.46	0.16	0.21	**0.24**	0.37
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.07)	(0.08)	**(0.06)**	(0.06)
	0.28	0.26	0.53	0.40	0.32	0.30	0.22	0.24	**0.07**	0.18
	0.38	0.37	0.42	0.41	0.38	0.38	0.49	0.44	**0.34**	0.32
	0.40	0.41	0.58	0.57	0.42	0.45	0.68	0.53	**0.35**	0.27
PRO $S1.0-r$ noinfo	0.13	0.17	0.07	0.01	0.03	0.08	0.24	0.19	0.15	**0.02**
	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)	(0.04)	(0.07)	(0.08)	(0.06)	**(0.05)**
	0.06	0.05	0.19	0.04	0.08	0.08	0.15	0.16	0.14	**0.02**
	0.31	0.31	0.34	0.39	0.28	0.25	0.47	0.45	0.32	**0.25**
	0.28	0.28	0.35	0.43	0.24	0.15	0.57	0.56	0.37	**0.17**

Notes: Differences between predicted and realized distribution over purchase prices when the search model is non-sequential search. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

B.2 Search without Priors Model

B.2.1 Search Cost Estimation

The estimation of search costs under the search without priors model is similar to that under sequential search. In both cases the search strategy is a reservation price policy. Suppose the DM searches n shops and her reservation value at the n'th shop equals r_n^{swp}. We assume $\theta = \frac{a}{b}$. For given parameter values ρ, κ, θ, her search cost parameter k from equation (23) equals

$$k^{\text{swp}}(r_n^{\text{swp}}, \rho, \kappa, n, \theta) = \frac{1+\kappa}{n^{1+\kappa} - (n-1)^{1+\kappa}} \left(\frac{1}{\Delta_F^{\rho}} \frac{1}{n} \frac{r_n^{\text{swp}} - \theta b}{2} + w \right). \tag{62}$$

Note that this equation is independent of the true price distribution, i.e., it also holds for the left- and right-skewed distributions as we have them in our experiment. The rest of the empirical model proceeds in the same manner as under sequential search.

B.2.2 Computations for the Search without Priors Model

Derivation of the distribution over the number of searches for given search cost parameter k, any price distribution. We derive the distribution over the number of searches for any distribution F from equality (62). For convenience, we write r_n instead of r_n^{nop}. From equation (62) we then get the reservation price at the n'th search

$$r_n = \theta b + 2\Delta_F^{\rho} nk. \tag{63}$$

We obtain an upper bound $\bar{k}_1$ for the search cost parameter when we set the reservation price at the first search equal to the highest possible price, $r_1 = b$:

$$\bar{k}_1 = \frac{b - \theta b}{2\Delta_F^{\rho}}. \tag{64}$$

It is optimal for the DM not to conduct any search if $k \geq \bar{k}_1$ and to conduct at least one search if $k < \bar{k}_1$. Denote by $\bar{n}_k$ the maximal number of searches the DM may conduct. This is the highest integer value n so that $\theta b + 2\Delta_F^{\rho} nk < b$. If $\bar{n}_k = 1$, the DM searches exactly one time. Suppose that $\bar{n}_k > 1$. In this case, the probability that the DM conducts exactly one search equals $\Pr(1; k) = F(r_2)$. The probability that she conducts $n \in \{2, ..., \bar{n}_k - 1\}$ searches is

$$\Pr(n; k) = (1 - F(r_{n+1}))^{n-1} F(r_{n+1}) + \sum_{x=1}^{n-1} \binom{n-1}{x} (F(r_{n+1}) - F(r_n))^x (1 - F(r_{n+1}))^{n-1-x}, \tag{65}$$

and the probability that she conducts $\bar{n}_k$ searches equals

$$\Pr(\bar{n}_k; k) = (1 - F(r_{\bar{n}_k}))^{\bar{n}_k - 1}. \tag{66}$$

Derivation of the distribution over purchase prices for given search cost parameter k, any price distribution. We derive the distribution over purchase prices. The DM does not conduct any search if $k \geq \bar{k}_1$ as defined in (64). The expected purchase price then equals b. Define

$$\bar{k}_n = \frac{b - \theta b}{2n\Delta_F^{\rho}}. \tag{67}$$

We obtain $\bar{k}_n$ by setting $r_n = b$ in equation (63). If $\bar{k}_1 > k \geq \bar{k}_2$, the DM searches exactly once and we have $F(p;k) = F(p)$ and $f(p;k) = f(p)$. If $\bar{k}_n > k \geq \bar{k}_{n+1}$, the maximal number of searches is $n \equiv \bar{n}_k$ and we get the following distribution over purchase prices:

$$F(p;k) = \begin{cases} F_1(p;k) & \text{if } p \in [a, r_2) \\ F_m(p;k) & \text{if } p \in [r_m, r_{m+1}) \text{ and } m \in \{2, ..., \bar{n}_k - 1\} \\ F_{\bar{n}_k}(p;k) & \text{if } p \in [r_{\bar{n}_k}, b] \end{cases}, \tag{68}$$

where

$$\begin{aligned} F_1(p;k) =& 1 - \sum_{n=1}^{\bar{n}_k - 1} \Bigg[(1 - F(r_{n+1}))^{n-1} (F(r_{n+1}) - F(p)) \\ &+ \sum_{x=1}^{n-1} \binom{n-1}{x} (F(r_{n+1}) - F(r_n))^x (1 - F(r_{n+1}))^{n-1-x} (1 - F(p)) \Bigg] \\ &- (1 - F(r_{\bar{n}_k}))^{\bar{n}_k - 1} (1 - F(p)), \end{aligned} \tag{69}$$

and

$$\begin{aligned} F_m(p;k) =& 1 - \Bigg[(1 - F(r_{m+1}))^{m-1} (F(r_{m+1}) - F(p)) \\ &+ \sum_{x=1}^{m-1} \binom{m-1}{x} (F(r_{m+1}) - F(p))^x (1 - F(r_{m+1}))^{m-1-x} (1 - F(p)) \Bigg] \\ &- \sum_{n=m+1}^{\bar{n}_k - 1} \Bigg[(1 - F(r_{n+1}))^{n-1} (F(r_{n+1}) - F(p)) \\ &+ \sum_{x=1}^{n-1} \binom{n-1}{x} (F(r_{n+1}) - F(r_n))^x (1 - F(r_{n+1}))^{n-1-x} (1 - F(p)) \Bigg] \\ &- (1 - F(r_{\bar{n}_k}))^{\bar{n}_k - 1} (1 - F(p)), \end{aligned} \tag{70}$$

and

$$F_{\bar{n}_k}(p;k) = 1 - (1 - F(p))^{\bar{n}_k}. \tag{71}$$

From this, we obtain the density over purchase prices for $\bar{k}_n > k \geq \bar{k}_{n+1}$ and $n \equiv \bar{n}_k$:

$$f(p;k) = \begin{cases} f_1(p;k) & \text{if } p \in [a, r_2) \\ f_m(p;k) & \text{if } p \in [r_m, r_{m+1}) \text{ and } m \in \{2, ..., \bar{n}_k - 1\} \\ f_{\bar{n}_k}(p;k) & \text{if } p \in [r_{\bar{n}_k}, b] \\ 0 & \text{else} \end{cases}, \tag{72}$$

where

$$\begin{aligned} f_1(p;k) =& f(p) \left[\sum_{n=1}^{\bar{n}_k - 1} \left((1 - F(r_{n+1}))^{n-1} \right. \right. \\ &+ \left. \left. \sum_{x=1}^{n-1} \binom{n-1}{x} (F(r_{n+1}) - F(r_n))^x (1 - F(r_{n+1}))^{n-1-x} \right) + (1 - F(r_{\bar{n}_k}))^{\bar{n}_k - 1} \right], \end{aligned} \tag{73}$$

and

$$\begin{aligned} f_m(p;k) =& f(p) \left[(1 - F(r_{m+1}))^{m-1} \right. \\ &+ \sum_{x=1}^{m-1} \binom{m-1}{x} \{x(F(r_{m+1}) - F(p))^{x-1} (1 - F(r_{m+1}))^{m-1-x} (1 - F(p)) \\ &+ (F(r_{m+1}) - F(p))^x (1 - F(r_{m+1}))^{m-1-x}\} \\ &+ \sum_{n=m+1}^{\bar{n}_k - 1} \{(1 - F(r_{n+1}))^{n-1} \\ &+ \left. \sum_{x=1}^{n-1} \binom{n-1}{x} (F(r_{n+1}) - F(r_n))^x (1 - F(r_{n+1}))^{n-1-x}\} + (1 - F(r_{\bar{n}_k}))^{\bar{n}_k - 1} \right], \end{aligned} \tag{74}$$

and

$$f_{\bar{n}_k}(p;k) = f(p)\, \bar{n}_k (1 - F(p))^{\bar{n}_k - 1}. \tag{75}$$

For simulating purchases through inverse transform sampling, we need to obtain $p = F^{-1}(u;k)$ in (68) for $u \in [0,1]$, which yields

$$p = \begin{cases} F_1^{-1}(u;k) & \text{if } u \in [F(a), F(r_2)) \\ F_m^{-1}(u;k) & \text{if } u \in [F(r_m), F(r_{m+1})) \text{ and } m \in \{2, ..., \bar{n}_k - 1\} \\ F_{\bar{n}_k}^{-1}(u;k) & \text{if } u \in [F(r_{\bar{n}_k}), F(b)] \end{cases} \tag{76}$$

which can be implemented sequentially by the fact that $F(p;k) = u$, so the initial case distinction in p-space can be used. The quantiles in (76) are obtained through piecewise inversion of the expressions in (69) to (71) in order to obtain $F(p) = u'$, and then to compute $p = F^{-1}(u')$.

B.2.3 Search Cost Estimation for the Search without Priors Model

We consider the same specifications as for the sequential search model and obtain estimated values of $\rho = 1.00$ and $\kappa = 0.00$. Table B5 provides an overview of the search cost estimates. To simplify the comparison, we also show the search cost estimates from the classic models as well as direct search costs in this table. Table B6 shows the detailed results from the search cost estimation with the search without priors model.

The estimated search costs for the November 2023 AMT sample vary between 0.15 USD and 0.18 USD, and for the June 2024 AMT sample they vary between 0.09 USD and 0.16 USD. In both cases, the differences between the respective information and no-information treatments are not statistically significant (p-values > 0.194). In the June 2024 PRO sample, search costs vary between 0.05 USD and 0.15 USD. The difference between the treatments PRO $S\,1.0 - l$ and PRO $S\,1.0 - l$.noinfo is not significant (p-value $= 0.211$), while the difference between PRO $S\,1.0 - r$ and PRO $S\,1.0 - r$.noinfo is statistically significant (p-value < 0.001). Therefore, the search without priors model does not equalize the search cost estimates between these treatments.

Table B5: Estimated Mean Search Costs and Direct Search Costs

Sample Treatment	Estimated Search Costs (sequential)	Estimated Search Costs (non-sequential)	Estimated Search Costs (s. w/o priors)	Direct Search Costs
AMT $S\,1.0$	0.185 (0.310)	0.219 (0.334)	0.179 (0.303)	0.228 (0.298)
AMT $S\,1.0$ – noinfo	0.169 (0.298)	0.192 (0.316)	0.153 (0.281)	0.207 (0.312)
AMT $S\,1.0 - l$	0.130 (0.298)	0.141 (0.314)	0.141 (0.266)	0.191 (0.273)
AMT $S\,1.0 - l$.noinfo	0.136 (0.306)	0.153 (0.327)	0.160 (0.283)	0.187 (0.223)
AMT $S\,1.0 - r$	0.100 (0.258)	0.129 (0.299)	0.093 (0.215)	0.197 (0.292)
AMT $S\,1.0 - r$.noinfo	0.101 (0.259)	0.123 (0.292)	0.096 (0.219)	0.163 (0.198)
PRO $S\,1.0 - l$	0.149 (0.285)	0.138 (0.257)	0.147 (0.232)	0.148 (0.126)
PRO $S\,1.0 - l$.noinfo	0.127 (0.258)	0.120 (0.233)	0.120 (0.205)	0.154 (0.198)
PRO $S\,1.0 - r$	0.184 (0.322)	0.202 (0.324)	0.136 (0.221)	0.144 (0.129)
PRO $S\,1.0 - r$.noinfo	0.067 (0.172)	0.081 (0.180)	0.048 (0.112)	0.123 (0.128)

Notes: Standard errors in parentheses. The search cost estimates for each model originate from the regressions in Table 3, Table 4, and Table B6, respectively. The last column shows the average direct search costs.

Table B6: Search Cost Estimates: Search without Priors

	(1)	(2)	(3)	(4)	(5)
$S1.0$	-2.33***		-2.62***		
	(0.21)		(0.34)		
$S5.0$	-0.55*		-2.89***		
	(0.25)		(0.34)		
$S1.0$ − noinfo	-2.69***		-3.14***		
	(0.21)		(0.32)		
$S1.0-l$				-3.35***	-2.85***
				(0.26)	(0.18)
$S1.0-r$				-4.37***	-2.97***
				(0.24)	(0.16)
$S1.0-l$.noinfo				-3.01***	-3.15***
				(0.27)	(0.16)
$S1.0-r$.noinfo				-4.29***	-4.30***
				(0.23)	(0.14)
β		-2.17***			
		(0.13)			
σ	2.71***	2.35***	3.14***	2.87***	1.68***
	(0.11)	(0.10)	(0.17)	(0.11)	(0.06)
κ		-0.00			
		(0.03)			
ρ		1.00***			
		(0.00)			
Data	AMT	AMT	AMT	AMT	PRO
Treatments	$S5.0$	$S5.0$	$S5.0$	$S1.0-l$	$S1.0-l$
	$S1.0$	$S1.0$	$S1.0$	$S1.0-r$	$S1.0-r$
	$S1.0$ − noinfo	$S1.0-pr4$	$S1.0$ − noinfo	$S1.0-l$.noinfo	$S1.0-l$.noinfo
		$S1.0-pr8$		$S1.0-r$.noinfo	$S1.0-r$.noinfo
		$S1.0-pr12$			
ρ est.	fixed 0	est.	fixed at est.	fixed at est.	fixed at est.
Observations	613	1015	613	802	562
Log.Lik.	-1565.32	-2934.17	-1536.51	-2198.06	-1367.91
AIC	3138.64	5876.34	3081.01	4406.12	2745.82
BIC	3156.32	5896.03	3098.69	4429.55	2767.48
SC $S5.0$	2.174		0.165		
	(4.001)		(0.292)		
SC 1.0	0.944		0.179		
	(2.566)		(0.303)		
SC $S1.0$ − noinfo	0.772		0.153		
	(2.288)		(0.281)		
SC $S1.0-l$				0.141	0.147
				(0.266)	(0.232)
SC $S1.0-l$.noinfo				0.160	0.120
				(0.283)	(0.205)
SC $S1.0-r$				0.093	0.136
				(0.215)	(0.221)
SC $S1.0-r$.noinfo				0.096	0.048
				(0.219)	(0.112)

Notes: Ordered probit regressions with truncation for the search without priors model. In the top panel, standard errors of the estimated parameters are in parentheses. The bottom panel presents the search cost estimates for each treatment, derived from the parameter estimates shown in the top panel. The first value represents the mean of the implied search cost distribution, with the standard deviation of the distribution provided in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

B.2.4 Evaluation of Search Cost Estimates for the Search without Priors Model

Table B7: Predicted versus Observed Distribution over Number of Searches

	Prediction Error		Difference predicted and realized distribution	
	Means (SD)	Medians	HD	KL
sequential search (in-sample)				
information treatments	1.84 (1.32)	1.40	0.30	0.27
no-information treatments	2.52 (1.48)	1.70	0.32	0.33
all treatments	2.18 (1.40)	1.55	0.31	0.30
non-sequential search (in-sample)				
information treatments	2.47 (1.31)	0.60	0.31	0.30
no-information treatments	1.79 (1.48)	0.30	0.33	0.36
all treatments	2.13 (1.39)	0.45	0.32	0.33
search without priors (in-sample)				
information treatments	2.09 (1.26)	0.60	0.28	0.25
no-information treatments	2.57 (1.44)	1.20	0.30	0.30
all treatments	2.33 (1.35)	0.90	0.29	0.27
sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	2.83 (1.41)	1.85	0.32	0.33
any treatment → any treatment	3.43 (1.38)	1.87	0.32	0.33
non-sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	2.86 (1.39)	1.25	0.34	0.38
any treatment → any treatment	3.84 (1.36)	1.42	0.33	0.36
search without priors (out-of-sample)				
inf./no-inf. → no-inf./inf.	2.95 (1.36)	1.40	0.31	0.31
any treatment → any treatment	4.30 (1.33)	1.87	0.31	0.33

Notes: Average differences between predicted and observed distribution over number of searches, as outlined in Subsection 4.2, for the classic search models as well as the search without priors model. The detailed values for each treatment combination for the latter model are presented in Table B9.

Table B8: Predicted versus Observed Distribution over Purchase Prices

	Prediction Error		Difference predicted and realized distribution	
	Means	Medians	HD	KL
sequential search (in-sample)				
information treatments	0.05 (0.06)	0.07	0.33	0.33
no-information treatments	0.09 (0.06)	0.10	0.32	0.32
all treatments	0.07 (0.06)	0.09	0.32	0.32
non-sequential search (in-sample)				
information treatments	0.16 (0.06)	0.08	0.36	0.39
no-information treatments	0.07 (0.06)	0.04	0.32	0.30
all treatments	0.12 (0.06)	0.06	0.34	0.34
search without priors (in-sample)				
information treatments	0.05 (0.06)	0.05	0.33	0.32
no-information treatments	0.07 (0.06)	0.05	0.31	0.31
all treatments	0.06 (0.06)	0.05	0.32	0.32
sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.09 (0.06)	0.09	0.33	0.32
any treatment → any treatment	0.13 (0.06)	0.14	0.33	0.33
non-sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.15 (0.06)	0.09	0.35	0.37
any treatment → any treatment	0.14 (0.06)	0.09	0.35	0.37
search without priors (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.11 (0.06)	0.07	0.34	0.35
any treatment → any treatment	0.15 (0.06)	0.13	0.34	0.36

Notes: Average differences between predicted and observed distribution over purchase prices, as outlined in Subsection 4.2, for the classic search models as well as the search without priors model. The detailed values for each treatment combination for the latter model are presented in Table B10.

Table B9: Observed vs. Predicted Number of Searches (Search w/o Priors)

$G^{[1]}$ $\hat{G}^{[1]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**2.70** **(1.52)** **0.00** **0.32** **0.32**	3.40 (1.62) 0.00 0.27 0.24	2.90 (2.15) 4.00 0.36 0.37	4.89 (2.14) 2.50 0.40 0.45	8.39 (1.66) 2.00 0.31 0.29	7.01 (1.63) 3.00 0.31 0.29	11.07 (1.03) 2.00 0.40 0.42	8.29 (1.30) 0.00 0.41 0.50	2.31 (0.44) 0.00 0.29 0.23	0.93 (0.72) 2.00 0.30 0.33
AMT $S1.0$ noinfo	0.84 (1.55) 1.00 0.32 0.31	**2.23** **(1.64)** **0.00** **0.26** **0.20**	1.62 (2.16) 4.00 0.34 0.33	0.84 (2.19) 1.50 0.41 0.48	6.80 (1.68) 2.00 0.29 0.26	6.81 (1.63) 3.00 0.31 0.30	13.69 (1.08) 3.00 0.41 0.42	11.24 (1.37) 1.00 0.40 0.48	2.96 (0.47) 0.00 0.29 0.22	0.48 (0.76) 2.00 0.28 0.26
AMT $S1.0-l$	0.74 (1.55) 1.00 0.33 0.33	3.68 (1.61) 0.00 0.28 0.24	**2.33** **(2.15)** **3.00** **0.35** **0.39**	1.90 (2.17) 0.50 0.43 0.57	7.35 (1.67) 2.00 0.29 0.29	7.50 (1.61) 3.00 0.31 0.33	12.31 (1.04) 3.00 0.40 0.41	9.02 (1.31) 1.00 0.38 0.39	3.96 (0.51) 0.00 0.30 0.23	0.31 (0.75) 2.00 0.28 0.24
AMT $S1.0-l$ noinfo	1.83 (1.53) 1.00 0.33 0.35	4.29 (1.60) 0.00 0.27 0.21	5.57 (2.12) 5.00 0.34 0.35	**3.93** **(2.15)** **2.00** **0.41** **0.47**	8.71 (1.65) 2.00 0.30 0.31	8.87 (1.59) 3.00 0.29 0.24	9.48 (0.98) 1.00 0.38 0.36	9.06 (1.33) 1.00 0.38 0.43	2.18 (0.41) 0.00 0.27 0.18	0.40 (0.72) 2.00 0.26 0.23
AMT $S1.0-r$	2.50 (1.59) 2.50 0.36 0.37	0.10 (1.65) 2.00 0.31 0.29	3.84 (2.22) 0.00 0.34 0.35	6.37 (2.24) 4.50 0.42 0.55	**4.57** **(1.69)** **0.00** **0.29** **0.24**	3.46 (1.66) 1.50 0.29 0.23	19.11 (1.14) 8.00 0.48 0.57	17.89 (1.43) 6.00 0.46 0.60	6.38 (0.58) 1.00 0.35 0.30	3.46 (0.83) 1.00 0.31 0.27
AMT $S1.0-r$ noinfo	2.22 (1.58) 3.00 0.36 0.37	0.71 (1.64) 2.00 0.29 0.25	4.50 (2.22) 0.00 0.34 0.35	5.20 (2.23) 3.50 0.42 0.56	4.66 (1.70) 1.00 0.29 0.27	**4.69** **(1.64)** **2.00** **0.28** **0.23**	17.56 (1.14) 6.00 0.45 0.49	17.22 (1.43) 6.00 0.45 0.56	6.45 (0.59) 1.00 0.35 0.30	2.15 (0.80) 1.00 0.28 0.23
PRO $S1.0-l$	6.80 (1.46) 0.00 0.22 0.08	9.26 (1.53) 1.00 0.27 0.21	13.21 (2.02) 6.00 0.36 0.59	12.47 (2.03) 3.50 0.39 0.44	11.54 (1.62) 3.00 0.28 0.12	11.22 (1.57) 4.00 0.28 0.14	**0.48** **(0.68)** **0.00** **0.25** **0.19**	1.07 (1.07) 1.00 0.30 0.28	0.66 (0.28) 1.00 0.17 0.11	4.02 (0.62) 2.00 0.31 0.45
PRO $S1.0-l$ noinfo	6.46 (1.46) 0.00 0.27 0.19	8.48 (1.53) 1.00 0.22 0.08	11.21 (2.03) 5.00 0.36 0.54	11.16 (2.04) 3.50 0.39 0.52	10.91 (1.62) 2.00 0.25 0.07	11.00 (1.57) 3.00 0.28 0.19	2.29 (0.72) 1.00 0.27 0.20	**0.80** **(1.11)** **1.00** **0.32** **0.32**	0.12 (0.28) 0.00 0.17 0.09	3.55 (0.62) 2.00 0.26 0.30
PRO $S1.0-r$	6.51 (1.46) 0.00 0.27 0.20	8.62 (1.53) 1.00 0.24 0.14	12.52 (2.02) 6.00 0.34 0.46	11.69 (2.03) 3.50 0.37 0.30	11.08 (1.62) 2.00 0.27 0.14	11.15 (1.57) 3.00 0.27 0.11	3.13 (0.75) 1.00 0.30 0.23	0.01 (1.10) 1.00 0.32 0.32	**0.35** **(0.28)** **0.00** **0.17** **0.09**	4.16 (0.62) 2.00 0.30 0.42
PRO $S1.0-r$ noinfo	3.28 (1.48) 2.00 0.34 0.32	4.78 (1.56) 2.00 0.32 0.35	4.17 (2.08) 0.00 0.38 0.53	3.02 (2.09) 2.50 0.43 0.72	8.82 (1.63) 1.00 0.29 0.27	8.75 (1.58) 2.00 0.25 0.11	9.80 (0.84) 5.50 0.41 0.44	8.55 (1.20) 4.00 0.42 0.50	2.19 (0.35) 1.00 0.29 0.24	**1.19** **(0.66)** **1.00** **0.25** **0.26**

Notes: Differences between predicted and realized distribution over the number of searches when the search model is search without priors. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

Table B10: Observed vs. Predicted Purchase Prices (Search w/o Priors)

$G^{[1]}$ / $\hat{G}^{[1]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**0.12**	0.10	0.20	0.12	0.32	0.32	0.20	0.08	0.11	0.29
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.07)	(0.08)	(0.06)	(0.06)
	0.05	0.03	0.18	0.06	0.13	0.13	0.20	0.18	0.09	0.04
	0.32	0.33	0.36	0.38	0.32	0.30	0.50	0.47	0.34	0.29
	0.30	0.33	0.42	0.45	0.28	0.26	0.68	0.64	0.43	0.24
AMT $S1.0$ noinfo	0.02	**0.04**	0.10	0.03	0.20	0.27	0.29	0.21	0.08	0.13
	(0.07)	**(0.07)**	(0.07)	(0.07)	(0.05)	(0.05)	(0.07)	(0.08)	(0.06)	(0.06)
	0.05	**0.06**	0.10	0.01	0.09	0.08	0.29	0.24	0.11	0.02
	0.31	**0.29**	0.35	0.40	0.29	0.29	0.52	0.46	0.32	0.28
	0.29	**0.28**	0.38	0.45	0.23	0.25	0.76	0.61	0.36	0.23
AMT $S1.0-l$	0.02	0.04	**0.12**	0.01	0.16	0.25	0.27	0.16	0.01	0.10
	(0.07)	(0.07)	**(0.07)**	(0.07)	(0.05)	(0.05)	(0.07)	(0.08)	(0.06)	(0.06)
	0.08	0.07	**0.14**	0.02	0.08	0.08	0.27	0.20	0.14	0.03
	0.32	0.30	**0.35**	0.39	0.28	0.27	0.52	0.46	0.32	0.27
	0.32	0.28	**0.38**	0.48	0.21	0.18	0.78	0.61	0.31	0.23
AMT $S1.0-l$ noinfo	0.03	0.01	0.24	**0.09**	0.23	0.27	0.13	0.12	0.07	0.19
	(0.07)	(0.07)	(0.07)	**(0.07)**	(0.05)	(0.05)	(0.08)	(0.08)	(0.06)	(0.06)
	0.06	0.00	0.22	**0.04**	0.12	0.11	0.14	0.18	0.06	0.01
	0.31	0.29	0.39	**0.41**	0.30	0.30	0.49	0.47	0.32	0.28
	0.29	0.23	0.46	**0.52**	0.23	0.25	0.67	0.67	0.33	0.23
AMT $S1.0-r$	0.14	0.20	0.03	0.22	**0.01**	0.05	0.50	0.41	0.17	0.00
	(0.07)	(0.07)	(0.07)	(0.07)	**(0.05)**	(0.04)	(0.07)	(0.08)	(0.06)	(0.05)
	0.17	0.16	0.07	0.37	**0.02**	0.01	0.64	0.62	0.21	0.08
	0.30	0.28	0.35	0.38	**0.24**	0.22	0.55	0.47	0.34	0.26
	0.21	0.21	0.38	0.48	**0.15**	0.11	0.85	0.64	0.38	0.22
AMT $S1.0-r$ noinfo	0.19	0.20	0.08	0.21	0.02	**0.05**	0.42	0.39	0.15	0.03
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	**(0.04)**	(0.07)	(0.08)	(0.06)	(0.05)
	0.18	0.14	0.19	0.37	0.02	**0.02**	0.47	0.50	0.20	0.07
	0.31	0.29	0.32	0.37	0.26	**0.21**	0.51	0.47	0.34	0.24
	0.30	0.27	0.33	0.37	0.19	**0.10**	0.73	0.66	0.37	0.17
PRO $S1.0-l$	0.12	0.11	0.36	0.22	0.28	0.24	**0.00**	0.06	0.01	0.20
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.04)	**(0.07)**	(0.08)	(0.06)	(0.05)
	0.15	0.18	0.39	0.22	0.26	0.19	**0.03**	0.00	0.01	0.13
	0.36	0.35	0.40	0.42	0.38	0.32	**0.44**	0.42	0.29	0.29
	0.34	0.36	0.51	0.56	0.45	0.34	**0.53**	0.47	0.25	0.22
PRO $S1.0-l$ noinfo	0.05	0.02	0.23	0.14	0.14	0.18	0.10	**0.06**	0.06	0.09
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.04)	(0.07)	**(0.08)**	(0.06)	(0.05)
	0.09	0.07	0.27	0.13	0.19	0.15	0.09	**0.09**	0.05	0.07
	0.34	0.32	0.40	0.40	0.35	0.30	0.45	**0.43**	0.29	0.26
	0.36	0.31	0.46	0.49	0.40	0.29	0.51	**0.51**	0.27	0.18
PRO $S1.0-r$	0.08	0.03	0.32	0.17	0.17	0.24	0.12	0.00	**0.02**	0.19
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.04)	(0.07)	(0.08)	**(0.06)**	(0.05)
	0.11	0.15	0.38	0.17	0.21	0.17	0.10	0.04	**0.00**	0.12
	0.37	0.33	0.38	0.37	0.35	0.31	0.46	0.43	**0.29**	0.29
	0.42	0.32	0.48	0.43	0.38	0.33	0.58	0.46	**0.26**	0.23
PRO $S1.0-r$ noinfo	0.30	0.32	0.12	0.24	0.09	0.05	0.51	0.43	0.29	**0.13**
	(0.06)	(0.06)	(0.07)	(0.07)	(0.05)	(0.04)	(0.07)	(0.07)	(0.06)	**(0.05)**
	0.13	0.10	0.00	0.18	0.05	0.02	0.51	0.38	0.18	**0.05**
	0.28	0.29	0.35	0.39	0.28	0.20	0.51	0.49	0.32	**0.23**
	0.14	0.24	0.40	0.50	0.24	0.10	0.70	0.68	0.40	**0.16**

Notes: Differences between predicted and realized distribution over purchase prices when the search model is search without priors. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

B.3 Restricted Number of Searches

Table B11: Average Search Outcomes – Restricted Number of Searches

Sample Treatment	Share Searchers	Mean and Median Rest. No. Searches		Diff. p-value
Information and No-Information Treatments				
AMT $S1.0$	0.972	2.49 (1.45)	2	0.451
AMT $S1.0$ – noinfo	0.957	2.60 (1.46)	3	
AMT $S1.0$ – l	0.980	3.08 (1.34)	4	0.342
AMT $S1.0$ – l.noinfo	1.000	2.95 (1.39)	4	
AMT $S1.0$ – r	0.975	2.77 (1.43)	4	0.674
AMT $S1.0$ – r.noinfo	0.995	2.83 (1.38)	4	
PRO $S1.0$ – l	0.922	3.02 (1.39)	4	0.510
PRO $S1.0$ – l.noinfo	0.918	3.13 (1.40)	4	
PRO $S1.0$ – r	0.954	2.20 (1.37)	2	0.000
PRO $S1.0$ – r.noinfo	0.963	2.86 (1.40)	4	
Piece Rate and Scale Treatments				
AMT $S0.2$ – $pr4$	0.917	2.25 (1.47)	2	–
AMT $S0.2$ – $pr8$	0.970	2.50 (1.46)	2	
AMT $S0.2$ – $pr12$	0.974	2.38 (1.44)	2	
AMT $S5.0$	0.974	2.50 (1.42)	2	

Notes: Standard deviation in parentheses. The p-value in the last column originates from a two-sided t-test which compares the mean restricted number of searches between an information treatment and the no-information treatment with the same price distribution.

Table B12: Predicted versus Observed Distribution over Restricted Number of Searches

	Prediction Error		Difference predicted and realized distribution	
	Means	Medians	HD	KL
sequential search (in-sample)				
information treatments	0.27 (0.12)	0.60	0.14	0.08
no-information treatments	0.30 (0.12)	0.80	0.17	0.09
all treatments	0.29 (0.12)	0.70	0.16	0.09
non-sequential search (in-sample)				
information treatments	0.12 (0.12)	0.20	0.17	0.12
no-information treatments	0.16 (0.11)	0.20	0.19	0.15
all treatments	0.14 (0.12)	0.20	0.18	0.14
search without priors (in-sample)				
information treatments	0.11 (0.12)	0.00	0.13	0.06
no-information treatments	0.09 (0.12)	0.40	0.17	0.11
all treatments	0.10 (0.12)	0.20	0.15	0.08
sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.37 (0.12)	0.80	0.17	0.12
any treatment → any treatment	0.34 (0.12)	0.92	0.17	0.11
non-sequential search (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.29 (0.12)	0.60	0.19	0.16
any treatment → any treatment	0.27 (0.12)	0.46	0.19	0.15
search without priors (out-of-sample)				
inf./no-inf. → no-inf./inf.	0.26 (0.12)	0.55	0.17	0.12
any treatment → any treatment	0.35 (0.12)	0.71	0.18	0.13

Notes: Average differences between predicted and observed distribution over the restricted number of searches, as outlined in Subsection 4.2, for the classic search models as well as the search without priors model. The detailed values for each treatment combination are presented in Table B13 to Table B15.

Table B13: Observed vs. Predicted Restricted Number of Searches (Sequential Search)

$G^{[1]}$ $\hat{G}^{[1]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**0.14**	0.26	0.74	0.49	0.62	0.64	0.66	0.71	0.03	0.67
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.14)	(0.13)	(0.12)	(0.12)
	0.00	1.00	2.00	1.00	2.00	2.00	1.00	1.00	0.00	2.00
	0.17	0.16	0.25	0.35	0.19	0.21	0.18	0.17	0.08	0.17
	0.11	0.09	0.20	0.29	0.14	0.15	0.12	0.11	0.02	0.12
AMT $S1.0$ noinfo	0.07	**0.21**	0.62	0.50	0.48	0.57	0.58	0.66	0.14	0.57
	(0.11)	**(0.11)**	(0.11)	(0.11)	(0.11)	(0.11)	(0.14)	(0.13)	(0.12)	(0.12)
	0.00	**1.00**	1.00	1.00	2.00	2.00	1.00	1.00	0.00	2.00
	0.16	**0.13**	0.23	0.36	0.17	0.19	0.17	0.16	0.07	0.15
	0.09	**0.06**	0.16	0.31	0.11	0.12	0.12	0.10	0.02	0.09
AMT $S1.0-l$	0.22	0.09	**0.26**	0.24	0.30	0.39	0.21	0.40	0.21	0.42
	(0.11)	(0.11)	**(0.11)**	(0.11)	(0.11)	(0.11)	(0.14)	(0.13)	(0.12)	(0.12)
	1.00	1.00	**0.00**	0.00	2.00	2.00	0.00	0.00	0.00	2.00
	0.15	0.10	**0.18**	0.29	0.14	0.16	0.10	0.11	0.08	0.12
	0.09	0.04	**0.11**	0.20	0.07	0.08	0.04	0.05	0.02	0.06
AMT $S1.0-l$ noinfo	0.08	0.03	0.32	**0.25**	0.37	0.45	0.23	0.41	0.20	0.38
	(0.11)	(0.11)	(0.11)	**(0.11)**	(0.11)	(0.11)	(0.14)	(0.13)	(0.12)	(0.12)
	1.00	0.00	0.00	**0.00**	2.00	2.00	0.00	0.00	0.00	2.00
	0.15	0.12	0.19	**0.29**	0.14	0.18	0.12	0.11	0.09	0.11
	0.08	0.06	0.12	**0.20**	0.07	0.10	0.06	0.05	0.03	0.05
AMT $S1.0-r$	0.50	0.18	0.07	0.08	**0.14**	0.18	0.04	0.17	0.41	0.21
	(0.11)	(0.11)	(0.10)	(0.11)	**(0.11)**	(0.10)	(0.14)	(0.13)	(0.12)	(0.12)
	2.00	1.00	0.00	0.00	**1.00**	1.00	0.00	0.00	1.00	1.00
	0.17	0.11	0.13	0.29	**0.13**	0.12	0.08	0.09	0.12	0.07
	0.13	0.04	0.06	0.22	**0.06**	0.05	0.03	0.03	0.06	0.02
AMT $S1.0-r$ noinfo	0.39	0.32	0.12	0.02	0.13	**0.20**	0.05	0.15	0.37	0.32
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	**(0.11)**	(0.14)	(0.13)	(0.12)	(0.12)
	2.00	1.00	0.00	0.00	1.00	**1.00**	0.00	0.00	1.00	1.00
	0.15	0.13	0.14	0.27	0.11	**0.11**	0.11	0.09	0.11	0.11
	0.10	0.07	0.07	0.19	0.04	**0.04**	0.05	0.03	0.05	0.04
PRO $S1.0-l$	0.06	0.20	0.66	0.52	0.73	0.69	**0.59**	0.73	0.14	0.77
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	**(0.14)**	(0.13)	(0.12)	(0.12)
	0.00	1.00	1.00	1.00	3.00	2.00	**1.00**	1.00	0.00	2.00
	0.15	0.14	0.22	0.32	0.22	0.23	**0.16**	0.19	0.05	0.21
	0.08	0.07	0.16	0.25	0.20	0.21	**0.10**	0.13	0.01	0.19
PRO $S1.0-l$ noinfo	0.03	0.04	0.57	0.28	0.54	0.61	0.48	**0.61**	0.04	0.67
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.14)	**(0.13)**	(0.12)	(0.12)
	0.00	0.00	1.00	0.00	2.00	2.00	1.00	**1.00**	0.00	2.00
	0.11	0.14	0.19	0.29	0.20	0.20	0.14	**0.17**	0.06	0.21
	0.05	0.07	0.13	0.22	0.15	0.16	0.08	**0.11**	0.01	0.17
PRO $S1.0-r$	0.29	0.41	0.85	0.71	0.80	0.84	0.77	0.94	**0.24**	0.96
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.14)	(0.13)	**(0.12)**	(0.12)
	0.00	1.00	2.00	2.00	3.00	3.00	2.00	2.00	**1.00**	3.00
	0.19	0.15	0.26	0.35	0.24	0.26	0.19	0.24	**0.08**	0.26
	0.13	0.09	0.22	0.30	0.24	0.26	0.14	0.22	**0.03**	0.29
PRO $S1.0-r$ noinfo	0.41	0.26	0.11	0.12	0.23	0.18	0.03	0.08	0.35	**0.23**
	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.10)	(0.14)	(0.13)	(0.12)	**(0.12)**
	2.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	**1.00**
	0.17	0.12	0.11	0.23	0.16	0.11	0.07	0.12	0.12	**0.13**
	0.12	0.06	0.05	0.17	0.09	0.05	0.02	0.05	0.06	**0.06**

Notes: Differences between predicted and realized distribution over the restricted number of searches when the search model is sequential search. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

Table B14: Observed vs. Predicted Restricted Number of Searches (Non-Sequential Search)

$G^{[1]}$ $\hat{G}^{[1]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**0.02** **(0.11)** **1.00** **0.24** **0.22**	0.05 (0.11) 0.00 0.19 0.14	0.30 (0.11) 0.00 0.19 0.12	0.19 (0.11) 0.00 0.31 0.25	0.52 (0.11) 2.00 0.24 0.19	0.50 (0.11) 2.00 0.28 0.23	0.31 (0.14) 0.00 0.10 0.04	0.39 (0.13) 0.00 0.13 0.06	0.12 (0.12) 0.00 0.21 0.17	0.69 (0.12) 2.00 0.21 0.15
AMT $S1.0$ noinfo	0.30 (0.11) 2.00 0.20 0.17	**0.08** **(0.11)** **1.00** **0.17** **0.12**	0.21 (0.11) 0.00 0.17 0.10	0.14 (0.11) 0.00 0.29 0.23	0.28 (0.11) 1.00 0.20 0.14	0.32 (0.11) 1.00 0.25 0.17	0.11 (0.14) 0.00 0.08 0.02	0.20 (0.13) 0.00 0.11 0.04	0.27 (0.12) 1.00 0.22 0.19	0.36 (0.12) 1.00 0.15 0.08
AMT $S1.0-l$	0.58 (0.11) 2.00 0.25 0.29	0.49 (0.11) 1.00 0.22 0.22	**0.21** **(0.10)** **0.00** **0.17** **0.12**	0.33 (0.11) 0.00 0.28 0.28	0.15 (0.11) 0.00 0.19 0.14	0.00 (0.11) 0.00 0.21 0.15	0.22 (0.14) 0.00 0.10 0.04	0.13 (0.13) 0.00 0.08 0.03	0.60 (0.12) 2.00 0.24 0.24	0.02 (0.12) 0.00 0.14 0.08
AMT $S1.0-l$ noinfo	0.57 (0.11) 2.00 0.26 0.30	0.39 (0.11) 1.00 0.19 0.15	0.08 (0.10) 0.00 0.15 0.09	**0.32** **(0.11)** **0.00** **0.29** **0.31**	0.05 (0.11) 0.00 0.19 0.13	0.11 (0.11) 1.00 0.21 0.15	0.11 (0.14) 0.00 0.10 0.04	0.02 (0.13) 0.00 0.08 0.02	0.60 (0.12) 2.00 0.24 0.25	0.09 (0.12) 0.00 0.12 0.05
AMT $S1.0-r$	0.62 (0.11) 2.00 0.26 0.30	0.52 (0.11) 1.00 0.21 0.20	0.30 (0.10) 0.00 0.19 0.17	0.40 (0.11) 0.00 0.25 0.22	**0.14** **(0.11)** **0.00** **0.19** **0.14**	0.08 (0.11) 0.00 0.20 0.14	0.35 (0.13) 0.00 0.12 0.06	0.14 (0.13) 0.00 0.08 0.03	0.81 (0.12) 2.00 0.27 0.33	0.04 (0.12) 0.00 0.11 0.05
AMT $S1.0-r$ noinfo	0.67 (0.11) 2.00 0.25 0.30	0.60 (0.11) 1.00 0.23 0.25	0.21 (0.10) 0.00 0.17 0.13	0.38 (0.11) 0.00 0.30 0.34	0.23 (0.11) 0.00 0.18 0.14	**0.17** **(0.10)** **0.00** **0.21** **0.16**	0.26 (0.14) 0.00 0.11 0.06	0.23 (0.13) 0.00 0.09 0.03	0.72 (0.12) 2.00 0.24 0.25	0.15 (0.12) 0.00 0.12 0.06
PRO $S1.0-l$	0.36 (0.11) 2.00 0.22 0.21	0.31 (0.11) 1.00 0.19 0.14	0.06 (0.10) 0.00 0.17 0.11	0.23 (0.11) 0.00 0.28 0.26	0.21 (0.11) 1.00 0.25 0.22	0.29 (0.10) 1.00 0.24 0.20	**0.11** **(0.14)** **0.00** **0.09** **0.03**	0.05 (0.13) 0.00 0.11 0.04	0.37 (0.12) 1.00 0.18 0.14	0.32 (0.12) 1.00 0.18 0.12
PRO $S1.0-l$ noinfo	0.53 (0.11) 2.00 0.23 0.24	0.38 (0.11) 1.00 0.18 0.14	0.14 (0.10) 0.00 0.15 0.09	0.25 (0.11) 0.00 0.25 0.22	0.06 (0.11) 1.00 0.21 0.16	0.20 (0.10) 1.00 0.25 0.21	0.22 (0.14) 0.00 0.11 0.05	**0.09** **(0.13)** **0.00** **0.13** **0.06**	0.42 (0.12) 1.00 0.17 0.13	0.21 (0.12) 1.00 0.18 0.11
PRO $S1.0-r$	0.05 (0.11) 1.00 0.23 0.20	0.06 (0.11) 0.00 0.22 0.17	0.29 (0.10) 1.00 0.19 0.13	0.21 (0.11) 1.00 0.31 0.28	0.69 (0.11) 2.00 0.29 0.30	0.71 (0.10) 2.00 0.31 0.33	0.23 (0.14) 0.00 0.11 0.05	0.32 (0.13) 1.00 0.18 0.11	**0.13** **(0.12)** **0.00** **0.17** **0.11**	0.78 (0.12) 2.00 0.26 0.28
PRO $S1.0-r$ noinfo	0.77 (0.11) 2.00 0.25 0.30	0.69 (0.11) 1.00 0.24 0.25	0.39 (0.10) 0.00 0.17 0.14	0.53 (0.11) 0.00 0.28 0.35	0.19 (0.11) 0.00 0.23 0.20	0.17 (0.10) 0.00 0.20 0.16	0.43 (0.13) 0.00 0.14 0.09	0.30 (0.13) 0.00 0.15 0.11	0.79 (0.12) 2.00 0.24 0.26	**0.15** **(0.12)** **0.00** **0.17** **0.12**

Notes: Differences between predicted and realized distribution over the restricted number of searches when the search model is non-sequential search. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.

Table B15: Observed vs. Predicted Restricted Number of Searches (Search w/o Priors)

$G^{[1]}$ $\hat{G}^{[1]}$	AMT $S1.0$	AMT $S1.0$ noinfo	AMT $S1.0-l$	AMT $S1.0-l$ noinfo	AMT $S1.0-r$	AMT $S1.0-r$ noinfo	PRO $S1.0-l$	PRO $S1.0-l$ noinfo	PRO $S1.0-r$	PRO $S1.0-r$ noinfo
AMT $S1.0$	**0.04** **(0.11)** **0.00** **0.18** **0.12**	0.13 (0.11) 0.00 0.15 0.08	0.21 (0.11) 0.00 0.19 0.12	0.10 (0.11) 0.00 0.28 0.20	0.64 (0.11) 2.00 0.22 0.16	0.63 (0.11) 2.00 0.24 0.19	0.13 (0.14) 0.00 0.09 0.04	0.33 (0.13) 0.00 0.10 0.04	0.10 (0.12) 0.00 0.12 0.05	0.75 (0.12) 2.00 0.20 0.15
AMT $S1.0$ noinfo	0.09 (0.11) 1.00 0.16 0.10	**0.05** **(0.11)** **0.00** **0.13** **0.06**	0.10 (0.10) 0.00 0.14 0.07	0.01 (0.11) 0.00 0.28 0.22	0.44 (0.11) 2.00 0.18 0.11	0.48 (0.11) 2.00 0.22 0.14	0.01 (0.14) 0.00 0.10 0.04	0.16 (0.13) 0.00 0.08 0.02	0.00 (0.12) 0.00 0.12 0.06	0.47 (0.12) 2.00 0.13 0.07
AMT $S1.0-l$	0.20 (0.11) 1.00 0.17 0.11	0.07 (0.11) 0.00 0.14 0.08	**0.07** **(0.10)** **0.00** **0.15** **0.08**	0.05 (0.11) 0.00 0.29 0.24	0.43 (0.11) 2.00 0.17 0.10	0.50 (0.11) 2.00 0.22 0.14	0.01 (0.14) 0.00 0.06 0.02	0.15 (0.13) 0.00 0.10 0.03	0.16 (0.12) 0.00 0.13 0.06	0.43 (0.12) 2.00 0.13 0.06
AMT $S1.0-l$ noinfo	0.08 (0.11) 1.00 0.17 0.11	0.01 (0.11) 0.00 0.15 0.08	0.21 (0.11) 0.00 0.18 0.12	**0.07** **(0.11)** **0.00** **0.29** **0.24**	0.55 (0.11) 2.00 0.20 0.14	0.65 (0.11) 2.00 0.22 0.16	0.12 (0.14) 0.00 0.08 0.03	0.27 (0.13) 0.00 0.10 0.04	0.01 (0.12) 0.00 0.11 0.05	0.54 (0.12) 2.00 0.15 0.08
AMT $S1.0-r$	0.41 (0.11) 2.00 0.19 0.15	0.31 (0.11) 1.00 0.14 0.08	0.09 (0.10) 0.00 0.14 0.08	0.35 (0.11) 0.00 0.27 0.27	**0.01** **(0.11)** **0.00** **0.12** **0.05**	0.13 (0.11) 0.50 0.14 0.06	0.32 (0.14) 0.00 0.14 0.08	0.17 (0.13) 0.00 0.08 0.03	0.52 (0.12) 1.00 0.16 0.11	0.21 (0.12) 1.00 0.08 0.03
AMT $S1.0-r$ noinfo	0.49 (0.11) 2.00 0.18 0.14	0.38 (0.11) 1.00 0.15 0.10	0.17 (0.10) 0.00 0.14 0.08	0.32 (0.11) 0.00 0.27 0.25	0.07 (0.11) 1.00 0.13 0.06	**0.09** **(0.11)** **1.00** **0.16** **0.09**	0.23 (0.14) 0.00 0.13 0.07	0.13 (0.13) 0.00 0.08 0.03	0.49 (0.12) 1.00 0.17 0.12	0.24 (0.12) 1.00 0.10 0.04
PRO $S1.0-l$	0.17 (0.11) 0.00 0.17 0.10	0.40 (0.11) 1.00 0.20 0.16	0.26 (0.10) 0.00 0.18 0.11	0.16 (0.11) 0.00 0.28 0.21	0.95 (0.11) 3.00 0.30 0.37	0.94 (0.10) 3.00 0.30 0.36	**0.21** **(0.14)** **0.00** **0.09** **0.03**	0.38 (0.13) 0.00 0.15 0.08	0.32 (0.12) 1.00 0.12 0.06	0.92 (0.12) 2.00 0.28 0.33
PRO $S1.0-l$ noinfo	0.02 (0.11) 0.00 0.19 0.13	0.12 (0.11) 1.00 0.15 0.08	0.10 (0.10) 0.00 0.17 0.10	0.00 (0.11) 0.00 0.26 0.20	0.68 (0.11) 2.00 0.25 0.25	0.79 (0.10) 2.00 0.28 0.31	0.03 (0.14) 0.00 0.07 0.02	**0.16** **(0.13)** **0.00** **0.13** **0.06**	0.11 (0.12) 0.00 0.07 0.02	0.71 (0.12) 2.00 0.23 0.22
PRO $S1.0-r$	0.09 (0.11) 0.00 0.18 0.12	0.18 (0.11) 1.00 0.17 0.10	0.20 (0.10) 0.00 0.16 0.09	0.02 (0.11) 0.00 0.28 0.23	0.81 (0.11) 2.00 0.28 0.32	0.86 (0.10) 2.00 0.28 0.31	0.06 (0.14) 0.00 0.09 0.03	0.31 (0.13) 0.00 0.13 0.06	**0.22** **(0.12)** **0.00** **0.09** **0.03**	0.92 (0.12) 2.00 0.27 0.32
PRO $S1.0-r$ noinfo	0.66 (0.11) 2.00 0.23 0.23	0.56 (0.11) 1.00 0.21 0.18	0.47 (0.10) 0.00 0.19 0.17	0.63 (0.11) 0.00 0.28 0.36	0.03 (0.11) 1.00 0.19 0.12	0.08 (0.10) 1.00 0.15 0.08	0.53 (0.13) 0.00 0.18 0.15	0.44 (0.12) 0.00 0.17 0.14	0.57 (0.12) 1.00 0.18 0.13	**0.07** **(0.12)** **1.00** **0.13** **0.08**

Notes: Differences between predicted and realized distribution over the restricted number of searches when the search model is search without priors. In each cell, the first number is the prediction error in means; the second number (in brackets) is the standard error of the point estimate of the prediction error in means; the third number is the prediction error in medians; the fourth (fifth) number indicates the Hellinger distance (Kullback-Leibler divergence) between the predicted and realized distribution.