Search Costs and Diminishing Sensitivity*

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Abstract

Empirical search cost estimates tend to increase in the size of the transaction even if search can be done conveniently online. To test whether there is a positive association between prices and search cost estimates, we conduct an online search experiment in which we manipulate the price scale while keeping the physical search effort for each price quote constant. For a sample of student subjects and for online workers at Amazon Mechanical Turk, standard search cost estimates indeed increase considerably in the price scale. To obtain scale-independent estimates, we modify the search model and allow for diminishing sensitivity, i.e., the tendency that people become less sensitive to price variations of fixed size when the price of the good increases. We find substantial degrees of diminishing sensitivity and heterogenous search costs. By combining average hourly earnings and the duration of search, we verify that the search cost estimates from the modified model capture subjects' true opportunity costs of time.

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1 Introduction

When price and product information is dispersed, consumers' search costs – the time and hassle cost of finding information – may limit the degree of competition between firms and hence the extent to which gains from trade are realized (Stigler 1961). However, in digital markets, search costs should be low since information on products and prices can easily be obtained online with a few clicks. At the dawn of online commerce, many economists therefore believed that the Internet would make markets more competitive and hence more beneficial for consumers (see, for example, the survey by Goldfarb and Tucker 2019).

So far, this prediction has not materialized. Price dispersion in digital markets is substantial, even in settings where acquiring price information is relatively simple; see Brynjolfsson and Smith (2000), Baye et al. (2004), Orlov (2011), Einav et al. (2015), and Jolivet and Turon (2019). The empirical literature that estimates consumer search costs from observational data finds large average search costs in digital markets for books (Hong and Shum 2006, De los Santos et al. 2012, Moraga-González et al. 2013), electricity contracts (Giulietti et al. 2014, Hortaçsu et al. 2017), hotels (Koulayev 2014, Ghose et al. 2017), automobile insurance (Honka 2014), and electronic articles (De los Santos et al. 2017, Jolivet and Turon 2019). An interesting feature of these search cost estimates is that their size increases in the value of the transaction.[1] The resulting search costs are often difficult to reconcile with the labor input that is necessary to identify and evaluate an alternative. For example, Hortaçsu et al. (2017) report that by investing 15 minutes into finding (and switching to) a cheaper energy provider, consumers could reduce their annual electricity costs by 100 USD.[2]

One may argue that such an increase is natural since more valuable products are also more complex. Alternatively, larger purchases may involve trust issues so that some consumers hesitate to buy an alternative even if it is cheaper and, on paper, offers the same quality and services. The sources cited above also use very different methods and data to identify search costs. However, we demonstrate in this paper that we obtain search cost estimates that increase in the price scale even when we keep the complexity of the product and the search process constant, trust issues do not arise, and the same method for estimating search costs is applied in all settings. This implies that at higher prices individuals do not fully take into account the benefits of (continued) search and therefore stop searching too early. We provide a behavioral explanation for this tendency and update the search cost model so that it generates scale-

[1] Here is an example. For books that are sold at prices between 8 and 23 USD, De los Santos et al. (2012) find search costs of around 1.35 USD per search. For computer chips sold at prices between 116 and 182 USD, Moraga-González et al. (2013) find search cost per search of around 8.70 USD. For electricity contracts with prices around 260 USD, Giulietti et al. (2014) document that 50 percent of customers exhibit search costs of at least 41.6 USD per search. This pattern also generalizes to switching, see Karle et al. (2021) for an overview.

[2] For comparison, the median hourly wage in the US in 2020 was only 19.33 USD.

independent search cost estimates. Finally, we show that these scale-independent search cost estimates correspond well with individuals' opportunity costs of time.

To obtain data on search and purchase prices in a setting where the price scale varies while everything else remains the same, we conduct an online search experiment. In this experiment, subjects can search for the lowest price of a (hypothetical) homogeneous product in up to 100 online shops. Their payoff in the experiment equals the price savings they realize. Our treatment variation is the price scale. It varies by a factor of seven between the treatments with the lowest and the highest price scale. The physical search costs (entering a 16-digit code at each online shop) are the same in all treatments. When deciding about search, subjects have complete information about the price distribution and the effort required to obtain a new price quote. They also have several days to complete their price search. We conduct the experiment both with a sample of student subjects and with a sample of online workers on Amazon Mechanical Turk (AMT). To estimate search costs, we use a standard search paradigm from the literature, random sequential search.[3]

Indeed, we find that search costs increase in the price scale. In the student sample, raising the price scale by a factor of seven increases the average estimated search costs per search by 134 percent. The average search costs in the highest scale treatment are 0.58 EUR per search and each search takes on average around 60 seconds, i.e., we obtain an implied average hourly reservation wage of around 35 Euros. In the AMT worker sample, raising the price scale by the same factor increases the average estimated search costs by even 795 percent. The average search costs in the highest scale treatment are 3.79 USD per search, where each search takes on average 85 seconds so that we get an implied average hourly reservation wage of around 161 USD. These results indicate that the empirical search cost model most likely does not correctly capture subjects' time and hassle costs of search and needs to be updated to mitigate the apparent contradictions.

To avoid search cost estimates that increase in price scale, we integrate "diminishing sensitivity" into the random sequential search model. Diminishing sensitivity implies that a certain amount of price savings appear large to a consumer when the price scale is small, but small when the price scale is large.[4] We propose diminishing sensitivity as the behavioral mechanism behind our results as it has been suggested repeatedly in the behavioral economics and psychological literature. First, diminishing sensitivity is, in varying configurations, an important feature of several non-standard preference models like reference-dependent loss aversion

[3]This search paradigm has been used, for example, by Hong and Shum (2006), Kim et al. (2010, 2017), Chen and Yao (2017), De los Santos et al. (2017), and Morozov et al. (2021).

[4]At a later stage, we also consider an alternative mechanism – relative thinking – to obtain scale-independent search cost estimates, see Section 7. Relative thinking and diminshing sensitivity have similar implications for a standard search setting, but their formalization is different.

(Kőszegi and Rabin 2006) and salience preferences (Bordalo et al. 2013). Second, diminishing sensitivity is also consistent with the Weber-Fechner law of psychophysics (Weber 1834, and Fechner 1860), which proposes that the intensity of a sensation increases linearly only in the logarithm of the energy that creates this sensation.[5] Third, diminishing sensitivity can explain choices in the famous "jacket-calculator vignette" explored by Thaler (1980), Tversky and Kahneman (1981), Azar (2011), and Shah et al. (2015). Thaler's (1980) version of this vignette goes as follows:

(a) You set off to buy a radio. When you arrive at the store, you find that the radio costs 25 USD, a price consistent with your priors. As you are about to make the purchase, a friend comes by and tells you that the same radio is selling for 20 USD at another store ten minutes away. Do you go to the other store? What is the minimum price differential which would induce to go to the other store? (b) Now suppose that instead of a radio you are buying a television for 500 USD, and your friend tells you it is available at the other store for 495 USD. Same questions.

Typical answers to these questions imply that people are more willing to realize the savings of 5 USD in the first situation than in the second situation. To obtain a search cost model that takes this behavioral tendency into account, we update the consumer's utility function from $u - p$ to $u - v(p)$, where u is the utility of the product, p the price that the consumer pays for the product, and v a concave function. To estimate the degree of diminishing sensitivity, we assume that v is a power utility function with constant γ that captures the degree of diminishing sensitivity.[6] For $\gamma = 0$, the model is identical to the standard sequential search model. For $\gamma = 1$, the search model would predict that search effort is independent of the price scale (this case would correspond to the Weber-Fechner law). We can use our data to jointly estimate search costs and the degree of diminishing sensitivity γ in the population. For this, we exploit the fact that search requires the same effort in all treatments.

From our sequential search model, we can bound reservation prices to lie between the lowest and second lowest discovered price. This gives rise to an ordered probit framework, enabling us to infer both search costs per search and the degree of diminishing sensitivity. We find a degree of diminishing sensitivity of $\gamma = 0.42$ in the student subject pool, and of $\gamma = 0.98$ among AMT workers. These values roughly equalize the search costs estimates in all treatments, and they also almost equalize search costs among student subjects and AMT

[5]The Weber-Fechner law has not been very prominent in economics. However, Thaler (1980) refers to it in the context of search, and recent theoretical as well as experimental work in economics finds connections to the Weber-Fechner law, e.g., Adriani and Sonderegger (2020) or Caplin et al. (2020).

[6]In expected utility theory, this variable would be the degree of constant relative risk aversion. This interpretation is not applicable in the present context.

workers. The resulting average search costs are 0.14 Euros per search in the student subject pool and 0.17 USD per search for AMT workers. These results imply that for expensive items standard search cost estimates partly reflect the price scale and not actual time and hassle costs. When we compare search cost estimates between the original and the modified model, we find for student subjects that in the highest scale treatment 77 percent of the original search costs are due to diminishing sensitivity. For AMT workers this share is even 95 percent.

The data from the AMT workers further allow us to evaluate whether the search cost estimates from the modified model capture the real time and hassle costs of search in our setting. The AMT workers in our sample work on average for 20 hours per week on AMT. Thus, they face a clear trade-off between searching and working in other jobs. We elicit from each AMT worker how much they earn on average in one hour by working on AMT. Additionally, we know for each AMT worker how much time she needs on average to obtain another price quote. Combining these two measures yields us a direct search cost measure for each individual AMT worker. The average value of this direct measure is 0.16 USD and hence remarkably close to the average search costs estimates from the modified model. We also find a significant positive correlation between an individual AMT worker's estimated search costs and her opportunity costs of time. Therefore, the search cost estimates from the modified model capture subjects' true time and hassle costs.

Related Literature. The paper contributes to growing literature that estimates physical search costs using the classic search models from the IO literature (e.g., Burdett and Judd 1983, Stahl 1989). This literature was initiated by Hong and Shum (2006) and largely uses observational data. Important contributions on search costs in online settings are De los Santos et al. (2012), Moraga-González et al. (2013), Giulietti et al. (2014), Honka (2014), Koulayev (2014), and Jolivet and Turon (2019). In contrast to these papers, we use data from an online search experiment. This allows us to vary the price scale, while keeping physical search costs constant. Moreover, our setting ensures that subjects know the price distribution at each shop as well as the required effort to find new price quotes. We therefore can cleanly identify the extent of scale-dependency of standard search cost estimates, that is, the complexity of products or biased beliefs cannot explain why estimated search costs increase in the price scale. Moreover, we record how much time subjects need to identify new price quotes. This allows us to derive a direct search cost measure to which we can compare the search cost estimates from the modified model.

There is also a large experimental literature on consumer search and search markets; see, e.g., Kogut (1990), Sonnemans (1998), Schunk and Winter (2009), and Brown et al. (2011) for the case of consumer search, and Davis and Holt (1996), Cason (2003), and Cason and Mago (2010) for the case of search markets. In this literature, search costs are implemented through monetary payments for each additional price quote. In contrast, we consider "real" hassle and time costs since subjects need to insert a 16-digit code to obtain a price quote. This allows us to study how the relationship between physical search costs and monetary gains of search changes in the price scale of products. Importantly, we consider an online search environment and give subjects several days for searching. The experimental setting is therefore very close to a generic online search environment.

On a more general level, the paper is related to the literatures on context effects (e.g., Bordalo et al. 2012, 2013, Kőszegi and Szeidl 2013, Dertwinkel-Kalt et al. 2017), relative thinking (Azar 2007, Bushong et al. 2021), and insensitivity to scale (Kahnemann et al. 1999, Schumacher et al. 2017). Context or relative thinking effects occur if changes in the choice set affect the preference order over a given set of options. Insensitivity to scale implies that decision-makers do not fully take into account the scale of an important outcome dimension when choosing between options. We consider these behavioral patterns in a search environment and examine some of their implications for empirical search cost estimates. In the main part of the paper, we use diminishing sensitivity to update the empirical search cost model. However, in an extension, we show that one can also use the "range-based relative thinking" model of Bushong et al. (2021, henceforth BSR) to obtain scale-independent search cost estimates. We briefly discuss the advantages and disadvantages of both approaches.

The rest of the paper is organized as follows. In Section 2, we describe the search model we use in our empirical analysis – random sequential search – and modify it by allowing for diminishing sensitivity. In Section 3, we describe our experimental design. In Section 4, we characterize our subject pool, average search behavior, and test to what extent search behavior conforms to sequential and non-sequential search. In Section 5, we estimate search costs in our online setting and the degree of diminishing sensitivity. In particular, we contrast the search cost estimates from the standard model with those from the modified model. In Section 6, we compare our search cost estimates with a direct measure of search costs that is derived from average hourly earnings and search duration. In Section 7, we replace diminishing sensitivity in our search cost model by a parametrized version of relative thinking to obtain scale-independent search cost estimates. Section 8 concludes. The instructions for the experiment as well as a number of additional analyses are relegated to the appendix.

2 Search and Diminishing Sensitivity

We consider a standard utility framework where the indirect utility function captures both utility from money and utility from leisure. Combining this indirect utility function with a standard search model – random sequential search – yields us the classic indifference condition for optimal search under this model. We then show how diminishing sensitivity with respect to prices affects this indifference condition (and hence search behavior). Using the indirect utility function we then also can derive the welfare effect of diminishing sensitivity.

2.1 Utility Framework and Sequential Search

We consider a decision-maker who can purchase a good for which she has unit demand. She can search for a lower price for this product. Search reduces leisure time and is therefore costly. Denote by L the total costs of search. They equal the time spent on search times the opportunity costs of time. If the decision-maker purchases the good at price p and spends L on search, her indirect utility equals

$$V(p, L) = u - \eta p - L, \tag{1}$$

where η is the marginal utility from money. Only this shape of the indirect utility function is consistent with a standard utility framework[7] when p is small relative to the decision-maker's total budget, and the time spent on search is small relative to her total available time. Following the literature, we normalize $\eta = 1$.

There is a (large) finite number of firms that offer the good at varying prices. Each firm chooses its price p according to the distribution $F(p)$ with support on $[a, b]$, where $b > a > 0$, and density $f(p)$. Before searching, the decision-maker does not know the firms' prices, only the price distribution $F(p)$. She can only purchase the good from a firm where she knows the price. We assume that search costs are constant so that we can write $L = nc$, where n is the number of searches and c is the costs per search, i.e., the required time to get a price quote times the opportunity costs of time. The assumption of constant search costs is plausible as long as the total time spent on search is small relative to the total available time.

We consider a classic search paradigm from the literature, namely random sequential search. Under this paradigm, the decision-maker chooses after each search whether to purchase the good at the lowest price discovered so far or to conduct one more search. The

[7]This utility framework would be as follows. A decision-maker has a budget of y that she can spend on a good g at price p for which she has unit demand, and on a numeraire $x \geq 0$ at normalized price one. Her budget constraint is $pg + x \leq y$. She also can spend time on search for a lower price of good g. Let p be very small relative to y and that the disutility from search is separable from the utility from consumption. The decision-maker's utility is given by $u(x, g) - L$, where the utility function u is continuously differentiable and strictly increasing in the first argument. We assume $u(x, 1) > u(x', 0)$ for any x, x' in the decision-maker's budget set. From a linear Taylor-approximation we get that the decision-maker's indirect utility function equals

$$V(p, y, L) \simeq u(y, 1) - u_1(y, 1)p - L,$$

where $u_1(y, 1) \equiv \eta$ is the marginal utility from income. For generic utility functions $u(x, g)$ and $p << y$ only this shape of the indirect utility function is consistent with unit demand for the good g.

indirect utility function in (1) implies that the optimal sequential search strategy is a reservation price policy, as in McCall (1970): There is a value $r \in [a, b]$ such that the decision-maker continues search as long as all previous prices exceeded r, and stops search as soon as a price is found that is weakly below r; the product is then purchased at this last price. The reservation price r is implicitly defined by the indifference condition

$$c = \int_a^r (r - p) f(p) dp. \tag{2}$$

The right-hand side of (2) captures the expected price savings from one more search if the current price is r, weighted by the marginal utility from consumption. If the current price is above r, the expected price savings from one more search exceeds c so that it is optimal to continue search; otherwise, it is optimal to stop search. We can calculate the value of the indirect utility function (1) at the optimal search strategy as

$$u - \mathbb{E}[p \mid p \leq r] - \frac{c}{F(r)}, \tag{3}$$

where r is defined by (2). The value in (3) is the expected payoff from following an optimal reservation price policy.

Before we introduce diminishing sensitivity, we briefly comment on an alternative search paradigm that is frequently considered in the theoretical and empirical literature, i.e., non-sequential search (or "fixed sample size search"). This search strategy has been introduced by Burdett and Judd (1983). Non-sequential search means that the decision-maker chooses the number n of price quotations that she wants to obtain. She then purchases the good at the lowest price in her sample. Under non-sequential search, the optimal number of searches minimizes the sum of search costs and expected purchase price (from an ex-ante perspective). In Subsection 4.2, we show that search behavior in our experiment is roughly consistent with sequential, but inconsistent with non-sequential search. Throughout the paper, we therefore focus on sequential search.

2.2 Diminishing Sensitivity

We now allow for diminishing sensitivity: When searching, the decision-maker may be less sensitive to price variations as the price level increases. Following the literature on behavioral welfare analysis (e.g., Bernheim and Taubinsky 2018), we capture this tendency in an indirect utility function that represents decision-utility, while assuming that experienced utility is still given by equation (1). Let decision utility be equal to

$$V^{ds}(p, L) = u - \eta v(p) - L, \tag{4}$$

where v is a strictly increasing and weakly concave function on the domain $[0, \infty)$. This specification implies that, while searching, the decision-maker perceives the difference between two prices $p - p'$ as $v(p) - v(p')$. If v is linear, we consider the standard case where the consumer is equally sensitive to price variations at all price levels. If v is strictly concave, this function captures diminishing sensitivity: As the price of the good increases the decision-maker becomes less sensitive towards price variations of fixed size. The decision-maker then no longer fully appreciates the gains from search. To formalize the shape of v, we will use the "power utility function" from expected utility theory. It is defined as

$$v(p) = \frac{p^{1-\gamma} - 1}{1 - \gamma}. \tag{5}$$

This function captures two important special cases. If $\gamma = 0$, we obtain the standard case where v is linear. If $\gamma = 1$, we obtain $v(p) = \ln p$. In this case, the decision-maker is equally sensitive to any given percentage price variation at all price levels. We will use this special case repeatedly to illustrate the consequences of diminishing sensitivity for search cost estimates. Finally, for $\gamma \in (0, 1)$ we obtain intermediate degrees of diminishing sensitivity.

The power utility function has been frequently used to model expected utility risk preferences with constant relative risk aversion. Therefore, it is important to point out that diminishing sensitivity in our framework is unrelated to risk preferences. We use the power utility function mainly for tractability reasons. However, when discussing the results from our experiment, we will comment on the potential role of risk preferences for search behavior (the theoretical and empirical literature on search mostly abstracts from risk preferences).

With diminishing sensitivity, the indifference condition in equation (2) that defines the reservation price r becomes

$$c = \int_a^r (v(r) - v(p)) f(p) dp. \tag{6}$$

If v is concave, then for given absolute price savings search becomes less attractive when the price level increases. Suppose that v is given by the power function in (5). For $\gamma = 0$ we obtain the classic indifference condition in equation (2). For $\gamma = 1$, we obtain *scale-independent search behavior*: Search behavior is determined by relative differences between prices, not by absolute differences. To see this, define by $\kappa > 1$ a parameter that scales up all prices that the decision-maker may observe. Since

$$\ln(\kappa r) - \ln(\kappa p) = \ln\left(\frac{\kappa r}{\kappa p}\right) = \ln(r) - \ln(p), \tag{7}$$

it follows that, at a reservation price of κr, the expected payoff from price savings from one more search is the same at any scale κ. The optimal reservation price is therefore equal to κr. The decision-maker then exhibits the same search behavior for prices scaled by $\kappa = 1$ and prices scaled by $\kappa > 1$: The probability that she conducts a certain number of searches is the same under both scales. This result does not arise under standard preferences, i.e., when $v(p) = p$. Furthermore, it does not depend on the distribution over prices $F(p)$.

Using our utility framework, we can calculate the welfare loss that is due to diminishing sensitivity. For given search costs c and degree of diminishing sensitivity γ, denote by r the reservation price defined by equation (2), and by r_γ the reservation price defined by equation (6). The decision-maker's (expected) experienced utility from search is then given by

$$u - \mathbb{E}[p \mid p \leq r_\gamma] - \frac{c}{F(r_\gamma)}. \tag{8}$$

The difference in the payoffs from (3) and (8) then equals the welfare loss from diminishing sensitivity:

$$\text{welfare loss} = \Big(\mathbb{E}[p \mid p \leq r_\gamma] - \mathbb{E}[p \mid p \leq r]\Big) + \left(\frac{1}{F(r_\gamma)} - \frac{1}{F(r)}\right)c. \tag{9}$$

Thus, the welfare loss consists of a change in the expected price and a change in the expected search costs. For example, if $r_\gamma > r$, so that the decision-maker searches too little relative to the rational benchmark, then the expected price increases while expected search costs decrease.

3 Experimental Design and Procedures

General Experimental Design. We recruit subjects to participate in an online search experiment. The experiment is split in two parts, Part 1 and Part 2. In Part 1, we collect demographic information (age, gender, education), as well as measures on cognitive ability and risk preferences. At the end of Part 1, subjects are informed about the design of Part 2; the detailed instructions for this part are in Appendix A.1. Part 2 takes place after the completion of Part 1.

In Part 2, subjects have to purchase a hypothetical product, which we call "Product A." They can search sequentially up to $N = 100$ online shops for the lowest price of this product. At each shop, prices are independently and uniformly distributed on the interval $[a, b]$ with

$b > a > 0$. Subjects are informed about this distribution. If they purchase Product A at price p, their payoff from Part 2 of the experiment is $b - p$. If they do not purchase the product, they automatically purchase it at the maximal price b so that their payoff from Part 2 is zero. After the start of Part 2, subjects have roughly four days for searching and purchasing the product.

The treatment variation is the price scale of the hypothetical product at the online shops. We define by α the lower and by β the upper bound on prices in a base treatment. Throughout, we will have $\alpha = 4$ and $\beta = 8$ (Euros or USD, depending on the subject pool). In scale treatment Sx for some $x > 0$, we have $a = x\alpha$ and $b = x\beta$. Each subject participates only in one treatment. Hence, we compare search behavior between-subjects. To get a price quote from an online shop, subjects have to enter a 16-digit code. This code is different for each shop and each subject. We disabled the "copy and paste" option so that subjects have to record the code in some way to insert it on the next page. This creates time and hassle costs of search. Upon entering the code, subjects see the price of the shop. They can then choose whether to purchase the good at this shop or to continue search or to purchase the good at a previously searched shop. They can access all previously searched shops without re-entering the code, so recall is essentially costless. In Part 1 of the experiment, we inform subjects about this procedure, and we ask them to enter an example code. Thus, they know in advance the physical costs of price search.

Since diminishing sensitivity is potentially a general feature of human behavior, it is important to show that our results also hold in a general population (Snowberg and Yariv 2021). To this end, we conduct the experiment with student subjects from Innsbruck EconLab and online workers at Amazon Mechanical Turk. Before starting the experiment, we registered it on aspredicted.org (registry number #68519) and obtained IRB approval from the Board for Ethical Questions in Science of the University of Innsbruck.

Student Subject Pool. Our first set of subjects are students from the University of Innsbruck recruited with the software hroot (Bock et al. 2014). We implemented four scale treatments with $x \in \{1.0, 3.0, 5.0, 7.0\}$. In the following, we call these treatments $S1.0$, $S3.0$, $S5.0$, and $S7.0$, respectively. The currency of all prices and payoffs of student subjects is Euros. The participation fee for the completion of the first part was 5 Euros. The second part of the experiment started one day after the end of the first part. We recruited 590 subjects who completed the first part; 150 subjects in $S1.0$, 149 in $S3.0$, 144 in $S5.0$, and 147 subjects in $S7.0$. They constitute our analytic sample for the experiment with student subjects.

AMT Subject Pool. Our second set of subjects are online workers on AMT. We implemented four scale treatments with $x \in \{0.5, 1.5, 2.5, 3.5\}$, and we call these treatments $S0.5$, $S1.5$, $S2.5$, and $S3.5$, respectively. The currency of all prices and payoffs of AMT workers is USD.

The participation fee for the completion of the first part was 1 USD. The second part of the experiment started right after the first part. Thus, subjects could complete both parts in one go.[8] We recruited 640 subjects who completed the first part; 145 subjects in $S0.5$, 164 in $S1.5$, 157 in $S2.5$, and 174 subjects in $S3.5$.

4 Preliminary Analysis

Before we estimate search costs, we describe our two subject samples and average search behavior in our experiment. In Subsection 4.1, we consider the demographics of student subjects and AMT workers. In Subsection 4.2, we examine to what extent subjects' search behavior is in line with sequential or non-sequential search. In Subsection 4.3, we examine some basic statistics on search effort in our setting.

4.1 Descriptive Statistics

We provide an overview of the demographics of our subjects. Table 1 shows the demographic variables of the two subjects pools. We show them for all subjects who completed Part 1 of the experiment and for all subjects who conducted at least one search in Part 2. Throughout the paper, we call the latter group "searchers" and the group of subjects who do not search at all "non-searchers." Overall, 84.2 percent of all student subjects and 83.0 percent of all AMT workers in our sample are searchers.[9]

[Insert Table 1 about here]

The students' subjects average age is 23.5 years and 62 percent of them are female. Their fields of study are diverse, around 50 percent are studying either economics or humanities. There are no significant differences in personal characteristics between searchers and non-searchers. The AMT workers' average age is 39.6 years and 44 percent of them are female. Their average education is relatively high. Around a quarter indicates to have a high school degree as highest educational degree, and three quarters indicate to have a Bachelor's degree or a higher degree. Again, there are no significant differences in these demographic variables between searchers and non-searchers.

[8] In a first version of this experiment on AMT, we implemented a time gap between the first and second part. Less than 60 percent of subjects started search in this setting even when the stakes were substantial (for AMT standards). To avoid this loss in observations and the risk of selection, we eliminated the time gap.

[9] From the set of searchers, we droped subjects who searched but did not purchase the product, and we droped subjects who purchased the product at a price that exceeds the smallest identified price by more than 0.10 Euros/USD. These are 9 student subjects and 14 AMT workers.

For both student subjects and AMT workers we elicit the general willingness to take risks (as measured by Dohmen et al. 2011) and cognitive ability through a cognitive reflection test (CRT). The willingness to take risks is measured on a scale between 0 and 10. The CRT comprises three questions, so the score in this test is between 0 and 3. Students' average willingness to take risks is 5.4, for AMT workers this value is 5.9. The average CRT score of both groups is also rather similar, around 2 correct answers out of 3 (which indicates that both groups are quite experienced). For student subjects, we again find no significant differences between searchers and non-searchers. For AMT workers, searchers are slightly less willing to take risks than non-searchers (one-sided t-test, p-value = 0.005).

We asked AMT workers in Part 1 about how much money they earn on average in an hour on AMT, and how many hours they work on AMT per week. On average they indicate that they earn 7.3 USD per hour (the median hourly earnings are 6.0 USD) and that they spend 20.8 hours per week working on AMT. Hourly earnings are not significantly different between searchers and non-searchers. However, the number of weekly hours on AMT is slightly lower among searchers than among non-searchers (one-sided t-test, p-value = 0.003).

To ensure that our samples are balanced between treatments, we compare the means of all variables both for all subjects and searchers only, see the Tables A1 and A2 in the Appendix. There are no significant differences in observable characteristics between treatments. This result also obtains in a linear regression framework. We therefore conclude that our samples are balanced between treatments.

4.2 Sequential versus Non-Sequential Search

We assess whether search behavior is more in line with sequential or non-sequential search. De los Santos et al. (2012) suggest three tests, which can be directly applied to our data. Test 1 to Test 3 below are directly taken from De los Santos et al. (2012), only the wording is slightly adjusted and Test 1 is extended to contrast the implications of sequential and non-sequential search.[10]

Test 1 (Recall)**.** *Under sequential search, a subject should not buy from a previously sampled shop, unless she has sampled all shops. Under non-sequential search, the probability of buying from the last sampled shop should not be significantly different from the probability of buying from any given previously sampled shop.*

Test 2 (Price Dependence I)**.** *Under sequential search, those subjects who search only once are more likely to have found a relatively low price than those subjects who search more than*

[10]De los Santos et al. (2012) distinguish between Test 2 and Test 3 since the latter can account for product differentiation. This does not matter for our setting, but for the sake of completeness we consider all tests.

once. Under non-sequential search, there should be no such association.

Test 3 (Price Dependence II)**.** *Under sequential search, subjects are more likely to continue search if the price at the current shop is relatively high. Under non-sequential search, there should be no such association.*

For Test 1, we find that 59.4 percent of student subjects and 87.7 percent of AMT workers indeed purchase from the last sampled shop or search all 100 shops (six student subjects did that). Therefore, search behavior is not perfectly in line with the sequential search paradigm. However, we also find that the probability of buying from the last sampled shop is much larger than the probability of buying from any given previously sampled shop. For student subjects, the latter probability is on average 4.9 percent, and the difference between the two probabilities is highly significant (one-sided t-test, p-value = 0.000). For AMT workers, the probability of buying from any given previously sampled shop is on average 5.9 percent and again much smaller than the probability of buying from the last sampled shop (one-sided t-test, p-value = 0.000). To illustrate these differences, we further differentiate between subject subgroups with a certain number of searches, see Table A3 in the Appendix.

With respect to Test 2, we find that that those subjects who search exactly once get on average a significantly lower price quote at the first shop than subjects who search more than once. For students, average prices are as follows: In treatment $S1.0$ the average price of one-time searchers is 4.76 Euros and the average price of all other searchers is 6.07 Euros. These numbers are 13.68 and 18.98 Euros in treatment $S3.0$, 23.24 and 31.22 Euros in treatment $S5.0$, and 30.60 and 42.26 Euros in treatment $S7.0$ (one-sided t-tests, p-values < 0.001). For AMT workers, the average price of one-time searchers in treatment $S0.5$ is 2.84 USD and 3.20 USD for all other searchers. These numbers are 8.29 and 9.81 USD in treatment $S1.5$, 14.73 and 15.98 USD in treatment $S2.5$, and 20.61 and 22.54 USD (one-sided t-tests, p-values $<$ 0.014). For both students and AMT workers, these results are confirmed in a linear probability regression model, see Column 1 and Column 2 of Table A4 and Table A5 in the Appendix.

For Test 3, we find that the probability of continuing search increases significantly, at any shop, in the observed price. To examine this test, we again consider a linear probability regression model, see Column 3 and Column 4 of Table A4 and Table A5 in the Appendix. For students, a one Euro increase in the observed price increases the probability of continuing search on average by 1.1 percent. This number is 7.4 percent, 1.8 percent, 1.3 percent, and 0.8 percent in the treatments $S1.0$, $S3.0$, $S5.0$, and $S7.0$, respectively. The corresponding coefficients are significant at the 1-percent level. For AMT workers, a one USD raise in the observed price increases the probability of continuing search on average by 4.4 percent. This number equals 23.1 percent, 7.9 percent, 5.1 percent, and 3.4 percent in the treatments $S0.5$, $S1.5$, $S2.5$, and $S3.5$, respectively. Again, the corresponding coefficients are all significant at the 1-percent level. We conclude that behavior in our experiment is roughly – not perfectly – consistent with the sequential search model, and inconsistent with non-sequential search.

4.3 Average Search Behavior

Table 2 summarizes subjects' average search behavior in our experiment. It shows the price scale for each treatment, the share of searchers, the average number of searches (provided that at least one search has been conducted), the median number of searches among searchers, and the average share of gains realized for those who conduct at least one search, that is, the value $(\bar{p} - a)/(b - a)$ where $\bar{p}$ is the average price paid by searchers.

[Insert Table 2 about here]

Among student subjects, the share of searchers does not vary significantly between the different treatments (one-way ANOVA, p-value = 0.747). The number of searches among those who search increases from around 7 in $S1.0$ to 11.5 in $S7.0$. This increase is significant (Jonckheere-Terpstra test, p-value = 0.006). However, it is partly driven by a small share of subjects who search a lot of shops. Six subjects search all 100 shops, two of them in $S3.0$, one in $S5.0$, and three in $S7.0$. Accordingly, the median number of searches only increases from 5 in $S1.0$ to 6 in $S7.0$. The average share of gains realized increases from 87 percent in $S1.0$ to 93 percent in $S7.0$ (Jonckheere-Terpstra test, p-value < 0.001). Hence, the amount of search slightly increases in scale, which suggests a degree of diminishing sensitivity γ below one.

Among AMT workers, the share of searchers again does not vary significantly between treatments (one-way ANOVA, p-value = 0.931). The number of searches among those who search neither increases nor decreases between $S0.5$ and $S3.5$ (Jonckheere-Terpstra test, p-value = 0.575). Surprisingly, the average share gains realized slightly decreases, from 68 percent in $S0.5$ to 65 percent in $S3.5$ (Jonckheere-Terpstra test, p-value = 0.084). These results suggest a degree of diminishing sensitivity γ close to one for AMT workers.

5 Estimating Search Costs

We now turn to the estimation of search costs. In Subsection 5.1, we derive lower and upper bounds on search costs, which we can directly infer from observed prices. In Subsection 5.2, we present the ordered probit model with which we can jointly estimate search costs and the degree of diminishing sensitivity. In Subsection 5.3, we present our estimation results. Finally, in Subsection 5.4, we consider a number of robustness checks.

5.1 Lower and Upper Bounds of Search Costs

In this subsection, we first show how search costs can be infered from reservation prices, for any degree of diminishing sensitivity γ, using the sequential search model from Section 2. We then use this link to derive lower and upper bounds on search costs for given $\gamma = 0$. We explicitly estimate search costs in the following subsections.

In each treatment of our experiment, prices are uniformly distributed on an interval $[a, b]$. Suppose that a subject's reservation price is given by $r \in (a, b)$. From equation (6), we get that for $\gamma = 0$, her search costs c equal

$$c(r) = \frac{(r-a)^2}{2(b-a)}. \tag{10}$$

For $\gamma = 1$, her search costs c would be equal to

$$c(r) = \frac{r - a + a(\ln a - \ln r)}{b-a}, \tag{11}$$

and for any $\gamma \in (0, 1)$, her search costs would be given by

$$c(r) = \frac{(1-\gamma)r^{2-\gamma} - (2-\gamma)ar^{1-\gamma} + a^{2-\gamma}}{(1-\gamma)(2-\gamma)(b-a)}. \tag{12}$$

If we could directly observe a subject's reservation price r, we could immediately back out, for given γ, her search costs from the above functions $c(r)$. Unfortunately, we do not observe r directly. Denote by $p^1, p^2, ..., p^n$ the set of observed prices, ordered from the smallest to the largest value (i.e., not in the order of detection). To characterize bounds on search costs, we have to distinguish between the following three cases. If a subject searches $n \in \{2, ..., 99\}$ times, her search costs must be in the interval $c(p^1) \leq c \leq c(p^2)$. If a subject searches exactly once, her search costs must be in the interval $c(p^1) \leq c \leq c(b)$. Finally, if a subject searches all 100 shops, her search costs must be in the interval $-\infty < c \leq c(p^1)$.

[Insert Table 3 about here]

To get an intuition for the search costs in our setting, we calculate for each treatment the mean lower and the mean upper bound on search costs for searchers, assuming that $\gamma = 0$. Table 3 shows the results. Among student subjects, the mean lower bound increases from 0.07 Euros in treatment $S1.0$ to 0.16 Euros in treatment $S7.0$. This increase is statistically significant (Jonckheere-Terpstra test, p-value < 0.001). Similarly, the mean upper bound on search costs increases from 0.59 Euros in treatment $S1.0$ to 2.85 Euros in treatment $S7.0$ (Jonckheere-Terpstra test, p-value $= 0.000$). For AMT workers, we find similar results. Their mean lower bound increases from 0.17 USD in treatment $S0.5$ to 1.47 USD in treatment $S3.5$, and their mean upper bound increases from 0.67 USD in treatment $S0.5$ to 5.00 USD in treatment $S3.5$ (Jonckheere-Terpstra test, p-value < 0.001 in both cases). We interpret these findings as an indication for diminishing sensitivity in both subject pools.

5.2 Ordered Probit Model

To jointly estimate search costs and the degree of diminishing sensitivity in our experiment, we now make a parametric assumption on the distribution of search costs across subjects. Using the sequential search cost model from Section 2, this will give rise to an ordered probit model. Specifically, we assume that the log of search costs is normally distributed and depends on a vector of subject characteristics x:

$$\ln c = x\beta + \sigma\varepsilon, \tag{13}$$

where ε follows a standard normal distribution Φ, β is a vector of parameters affecting the mean and σ is the standard deviation of the distribution. This assumption is common in the search costs literature and justified in our sample through a Box-Cox test nesting the normal and log-normal distribution of search costs. We find that for all specifications, the Box-Cox test indicates a log-normal distribution of search costs. For the number of searches $n \in \{2, ..., 99\}$, we observe the two smallest prices p^1, p^2 and get the following likelihood contribution

$$\begin{aligned} \Pr(c(p^1) \leq c < c(p^2)) &= \Pr\left(c(p^1) \leq \exp(x\beta + \sigma\varepsilon) < c(p^2)\right) \\ &= \Phi\left(\frac{\ln c(p^2) - x\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p^1) - x\beta}{\sigma}\right). \end{aligned} \tag{14}$$

For the censored observations with $n = 1$, we use

$$\begin{aligned} \Pr(c(p^1) \leq c < c(b)) &= \Pr\left(c(p^1) \leq \exp(x\beta + \sigma\varepsilon) < c(b)\right) \\ &= \Phi\left(\frac{\ln c(b) - x\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p^1) - x\beta}{\sigma}\right). \end{aligned} \tag{15}$$

Similarly, for $n = 100$, we use

$$\Pr(c < c(p^1)) = \Pr\left(\exp(x\beta + \sigma\varepsilon) < c(p^1)\right) = \Phi\left(\frac{\ln c(p^1) - x\beta}{\sigma}\right). \tag{16}$$

With log-normally distributed search costs, subjects always have positive search costs, so there will be relatively few subjects who search all shops. Those who search 100 times are just those who satisfy at least one of the following two conditions: they have very negative realizations of ε, so search costs are close to zero, or they had unlucky draws of prices all the time, so p^1 never became sufficiently low.

5.3 Estimation Results

In this subsection, we describe the results from our ordered probit regressions. We start with the standard case without diminishing sensitivity, $\gamma = 0$. Table 4 shows the results. The constant in Column 1 indicates the average search costs in both subject pools. When diminishing sensitivity is ignored, student subjects incur on average search costs of 0.46 Euros per search and AMT workers even 2.30 USD per search. There is considerable heterogeneity in search costs. We estimate a standard deviation around the mean of 2.00 for student subjects and of 8.65 for AMT workers.

The estimated search costs differ substantially between treatments, see Columns 2 of Table 4. For student subjects, the average search costs per search are only 0.25 Euros in treatment $S1.0$ and they reach 0.58 Euros in treatment $S7.0$, an increase of 134 percent. Similary, for AMT workers, the average search costs per search are 0.42 USD in treatment $S0.5$ and 3.79 USD in treatment $S3.5$, an increase of around 795 percent. These differences are statistically significant in both cases (p-value < 0.006 and p-value $= 0.000$, respectively). Column 3 shows the ordered probit regression results when we add our standard controls: a dummy for above-median age, gender, and dummies for above-median willingness to take risks and CRT score. We obtain roughly the same results when we include these controls. Hence, under the standard random sequential search model without diminishing sensitivity, empirical search cost estimates increase in the price scale even though the physical search costs remain constant. The estimation may capture a misspecification bias from not accounting for scale effects. We therefore now allow for flexible degrees of diminishing sensitivity.

[Insert Table 4 about here]

Column 1 of Table 5 shows the results from our ordered probit regressions with flexible γ for both subject groups. For student subjects, we find a degree of diminishing sensitivity of $\gamma = 0.42$ and average search costs per search of 0.14 Euros. The diminishing sensitivity parameter is significantly different from zero (p-value < 0.001), but also significantly smaller than one, the value proposed by the Weber-Fechtner law. For AMT workers, the ordered probit regressions yield us a degree of diminishing sensitivity of $\gamma = 0.98$ and average search costs per search of 0.17 USD. This degree of diminishing sensitivity is again different from zero (p-value $= 0.000$) and very close to the value suggested by the Weber-Fechtner law.

In Column 2 of Table 5 we consider the results from the same regression where we additionally take our standard control variables into account. For student subjects, none of these control variables is significant. For AMT workers, we find that the dummy variables for above-median willingness to take risks (coefficient = 0.10, se = 0.04) and above-median CRT score (coefficient = -0.05, se = 0.03) are statistically significant. These results suggest that subjects who are more willing to take risks have higher search costs, and that subjects with a higher CRT score tend to have lower search costs. Nevertheless, the control variables do not seem to explain much of the heterogeneity in search costs, as can be seen from our estimate of the standard deviation which remains essentially unchanged.[11]

[Insert Table 5 about here]

We can now compare the estimated search costs from the modified model with those from the standard model. Table 6 shows the results in Column 1 for student subjects and in Column 3 for AMT workers. In Columns 2 and 4, we again show the regression results under the assumption that $\gamma = 0$ (i.e., Column 2 from Table 4) to facilitate the comparison between the models. For student subjects, the average search costs per search vary between 0.12 Euros and 0.16 Euros. As expected, the differences are never significant (p-value > 0.367). For AMT workers, the average search costs per search vary between 0.14 USD and 0.19 USD. Again, these differences are not significant (p-value > 0.100). The estimated search costs are substantially smaller when we allow for diminishing sensitivity. In the highest scale treatments, a large part of the standard search cost estimates are due to scale: 77 percent in $S7.0$ for student subjects, and 95 percent in $S3.5$ for AMT workers. Finally, note that the estimated search costs are quite similar for students and AMT workers.[12] In contrast, when we assume $\gamma = 0$, the average search costs of AMT workers are 4.4 times larger than those of student subjects.

[Insert Table 6 about here]

To get an overview of the search cost distribution, we derive for each searcher the individual expected search costs per search using the two smallest observed prices p^1, p^2 and the estimated distribution over search costs from the ordered probit regressions. That is, we calculate the expected search costs conditional on the fact that they are in the interval $[c(p^1), c(p^2)]$, see Appendix A.2 for formal details. Figure 1 shows this distribution for student subjects and AMT workers. There is substantial heterogenity in both subject pools. For student subjects, the distribution has a single peak around very small search costs. For AMT workers, the distribution exhibits two peaks, one around very small search costs and one around 0.08 USD.

[11]We also considered a specification where we interact γ with the control variables. None of them plays a significant role. Hence, there is no heterogeneity in γ along our control variables.

[12]The exchange rate when the experiment took place on AMT was around 1.13 USD per Euro.

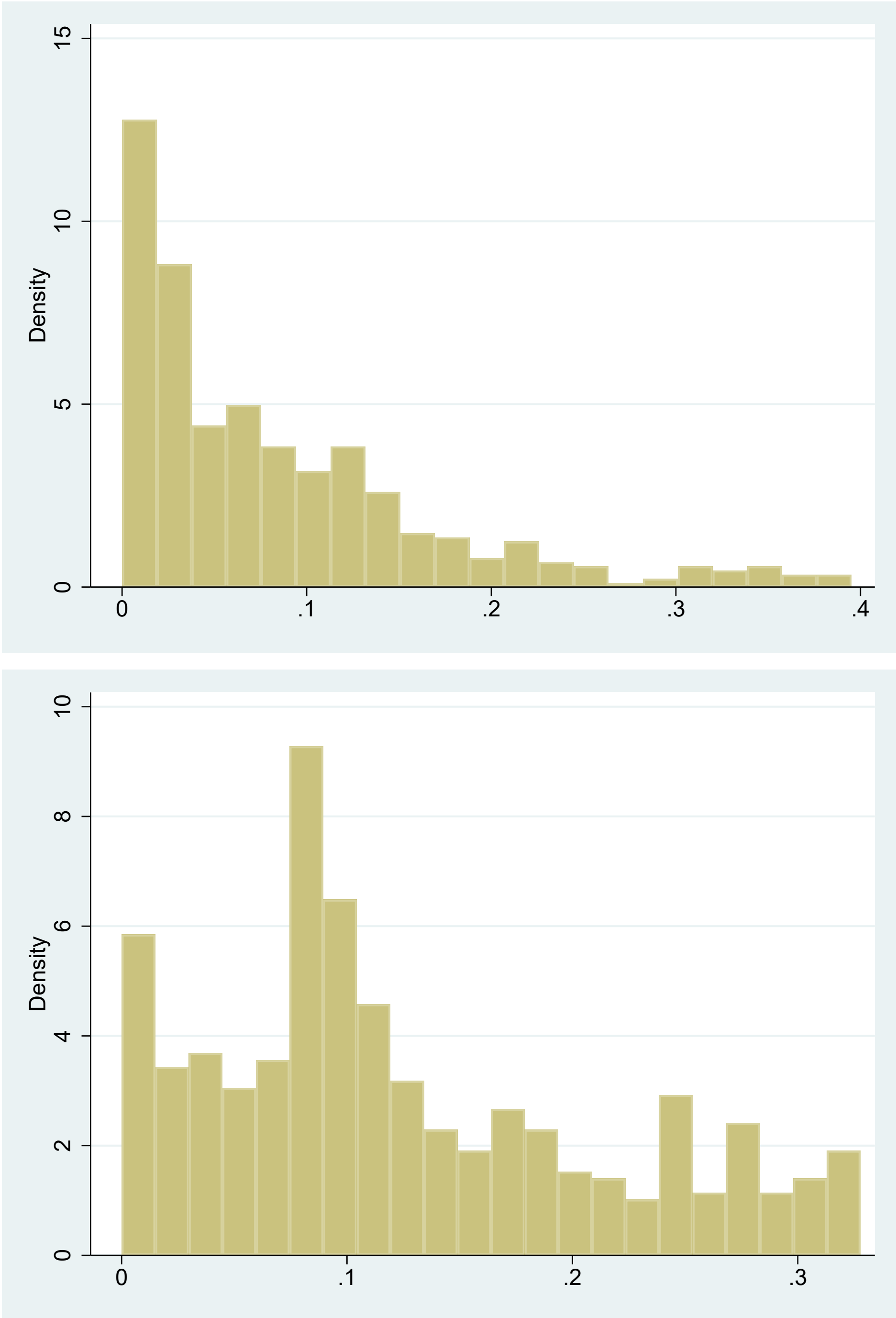

Figure 1: Distribution of expected individual search costs per search for student subjects (upper graph) and AMT workers (lower graph), for flexible degrees of diminishing sensitivity.

5.4 Robustness

We discuss a number of factors that may influence our estimation results. For the sake of brevity, we do not show the regression results of this subsection. They are available upon request from the authors.

Composition of Treatments. We used the data from all treatments to jointly estimate search costs and the degree of diminishing sensitivity. One also could run the experiment with other scale variations. It is therefore unclear to what extent our results depend on the composition of treatments. To examine whether our results are robust to variations in the treatment composition, we run our ordered probit regressions with only two instead of four scale treatments. It turns out that we obtain very similar estimation results as long as the two scales are sufficiently different. For student subjects we get the following results:

treatments used for estimation	estimated dim. sensitivity	estimated search costs
Panel A: Student Subjects		
$S1.0$ and $S7.0$	$\gamma = 0.42$	$c = 0.12$
$S1.0$ and $S5.0$	$\gamma = 0.48$	$c = 0.11$
all	$\gamma = 0.42$	$c = 0.14$
Panel B: AMT Workers		
$S0.5$ and $S3.5$	$\gamma = 1.02$	$c = 0.16$
$S0.5$ and $S2.5$	$\gamma = 1.01$	$c = 0.17$
all	$\gamma = 0.98$	$c = 0.17$

We therefore need only two treatments to estimate search costs and the degree of diminishing sensitivity in our search experiment. However, when we use scale treatments that are closer to each other than those used above, estimation results become more diverse (or may even become meaningless, e.g., when the estimated value of γ is negative).

Economics Students. We obtain quite different degrees of diminishing sensitivity for student subjects and AMT workers. One could suspect that this is due to the presence of economics students in the former sample (30 percent of searchers are economics students). These students may be better at making payoff-maximizing choices. Indeed, they behave differently than other subjects in some experimental settings (e.g., Baumann and Rose 2011). To study whether this is also the case in our setting, we run our ordered probit regression and include subject field dummies so that we can examine the degree of diminishing sensitivity of students with varying study subjects. It turns out that there are no significant differences between the estimated values of γ of different study subjects. Therefore, the difference between student subjects and AMT workers cannot be explained with the presence of economics students.

6 Search Time and Average Hourly Earnings

In the experiment, we precisely record the time subjects need to insert the 16-digit code to get another price quote. For AMT workers, we additionally observe (self-stated) average hourly earnings. We can use these data to calculate a direct measure of search costs per search. This measure does not depend on the prices that an AMT worker observed during her search. We can therefore compare our search cost estimates from the previous section to an objective opportunity cost measure to evaluate their validity.

This section is organized as follows. In Subsection 6.1, we first describe how much time subjects on average need to get a price quote and how much time they spend on search in the different treatments. In Subsection 6.2, we derive the direct search cost measure, and compare it to our search cost estimates from the previous section, both on the aggregate and the individual level.

6.1 Descriptive Statistics on Search Time

Table 7 provides an overview of several key search duration variables. The "mean search duration" is the average time it takes a subject from entering an online shop to discovering the price at this shop. The "mean total duration" is the time between entering the overview page and buying the product. The table also shows the median of these variables. For the mean search duration, we exclude searches that took longer than 10 minutes, and for the mean total duration we excluded searchers who took longer than 100 minutes.

[Insert Table 7 about here]

The mean search duration for students is roughly 60 seconds, and for AMT workers 85 seconds. There are no significant differences between treatments (one-way ANOVA, p-value = 0.626 for students, and p-value = 0.700 for AMT workers). For students, the results for total duration largely mirror those for the number of searches. Student subjects spend significantly more time on search in higher scale treatments (Jonckheere-Terpstra test, p-value < 0.001), but the increase in search time is modest and is partly driven by a few subjects who search extensively in high scale treatments. For AMT workers, there are no significant differences in mean total duration between treatments (one-way ANOVA, p-value = 0.788). For student subjects, the median total duration is around 6 minutes in treatment $S1.0$, and around 1.5 minutes longer in treatment $S7.0$. For AMT workers, the median total duration is between 2.5 and 3 minutes in all treatments.

6.2 Comparison of Search Cost Measures

For each AMT worker, we derive a direct search cost measure from her opportunity costs of one hour work on AMT and the time she needs on average to obtain a price quote. This search cost measure is given by

$$\text{direct search costs} = \text{average hourly earnings} \times \frac{\text{mean search duration}}{3600}. \tag{17}$$

It captures the amount of money the searcher could earn by working in another job on AMT instead of searching one more shop. Note that it does not use any variable that we used in our search cost estimation in Section 5.

We find that the average direct search costs of the AMT workers in our sample are 0.16 USD (sd = 0.28), which is surprisingly close to our estimated average search costs per search of 0.17 USD from the previous section when we allow for diminishing sensitivity. The upper graph of Figure 2 shows the distribution over direct search costs. For comparison, the lower graph again shows the distribution of search costs for AMT workers estimated from our search cost model. Both distributions are right skewed and share a similar support. Therefore, allowing for diminishing sensitivity does not only avoid scale dependece of search costs, but also generates search cost estimates that reflect the AMT workers' opportunity costs of time.

[Insert Table 8 about here]

Next, we examine the association between the two search cost measures. There should be a positive correlation between direct and estimated search costs. Table 8 shows the results from a linear regression where direct search costs is the dependent variable and estimated search costs the independent variable. Column 1 shows the regression results when no further controls are included, Column 2 the results when we add our standard controls. In both cases, we indeed find a positive association between the search cost measures. It is significant at the 10 percent level. For each one USD increase in estimated search costs there is a 0.54 USD (0.42 USD) increase in direct search costs according to the model without (with) controls. There is, however, a lot of unexplained heterogeneity as can be seen from the low R^2 values. A possible explanation for this is heterogeneity in the extent to which AMT workers enjoy doing the search task in our experiment relative to other jobs on AMT.

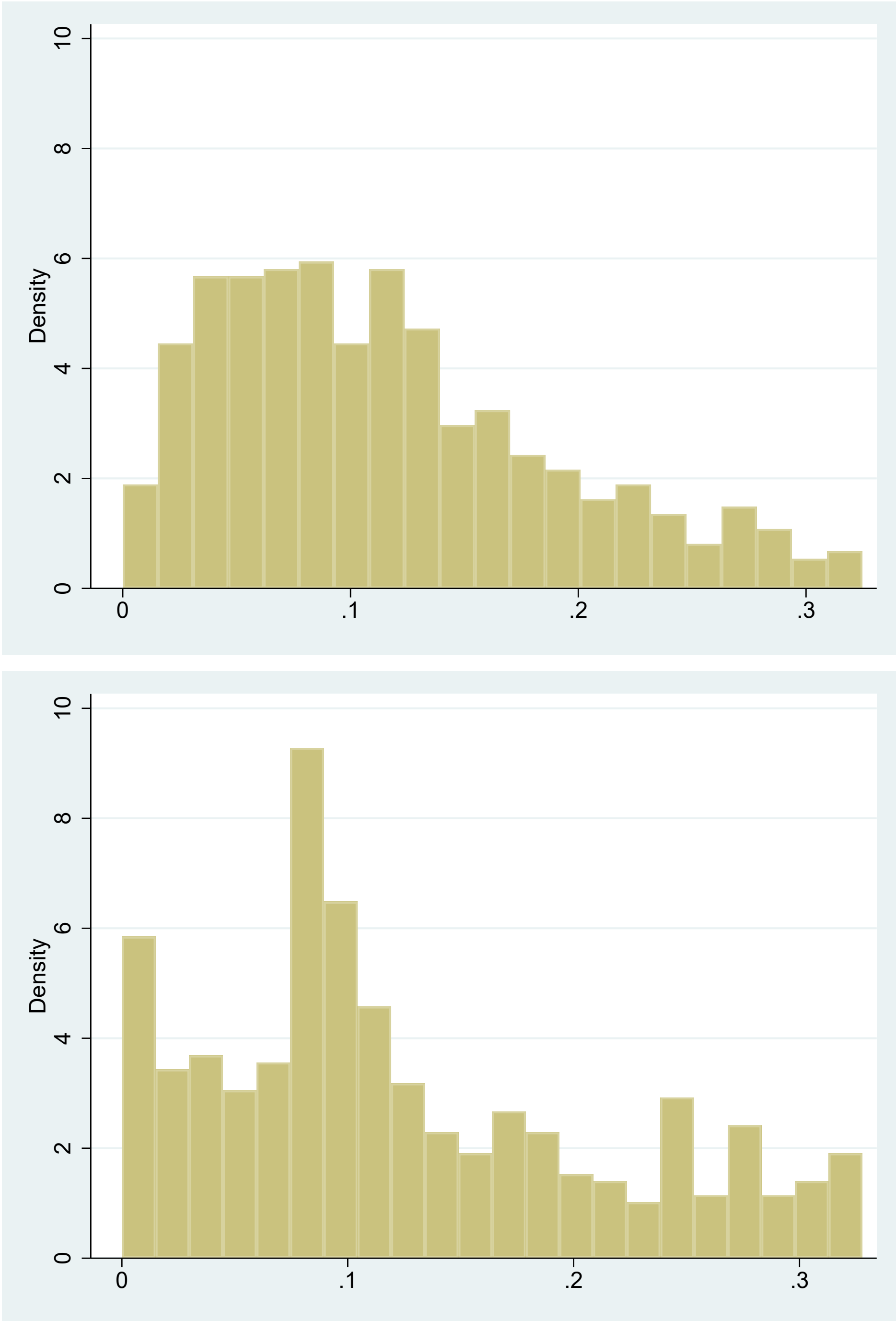

Figure 2: Direct search costs (upper graph) and expected individual search costs for flexible degrees of diminishing sensitivity (lower graph) of AMT workers.

Overall, these results suggest that it is possible to anchor search cost estimates in reasonable measures of search duration and opportunity costs of time. This is particularly convenient to do for the AMT workers in our sample since they spend substantial time working on AMT (more than 20 hours per week on average) and there is a clear trade-off between searching and working in other jobs. In many real-world settings, this trade-off is probably less clear. Nevertheless, for classic search cost estimates, one option to evaluate whether the time and hassle cost estimates are reasonable is to examine how much time it takes to identify another price or product. If the estimated search costs are very large relative to this duration, then it is likely that some informational friction (e.g., incomplete information regarding the choice set, search procedure, or seller reputation) causes a misspecification bias.

7 Relative Thinking and Search Cost Estimates

In order to obtain scale-independent search cost estimates, we allowed for diminishing sensitivity with respect to prices in the decision-maker's indirect utility function. Diminishing sensitivity is a behavioral pattern that is assumed in several theories of choice. There exist, however, alternative theories that can rationalize scale-dependent search costs. In a recent paper, Bushong et al. (2021) formalize a utility theory of "range-based relative thinking." In this model, the decision-maker's utility weight on the outcome of a given consumption dimension (such as money or leisure) depends on the variability of the outcomes in this dimension. This variability is defined by the choice set or the context. The larger the variability of outcomes, the smaller is the weight. Saving a given amount by exerting effort then appears less desirable if the range of prices is large than if it is small. In the context of price search, relative thinking therefore has similar implications as diminishing sensitivity.

We demonstrate in this section that – under some parametric assumptions – the BSR model can be used to obtain scale-independent search cost estimates in our experimental setting. This implies that we can use our data to obtain an estimate of the weighting function of the BSR relative thinking model. In Subsection 7.1, we first adapt this model to the random sequential search setting. In Subsection 7.2, we then present our search cost estimates and briefly discuss the advantages and disadvantages of the two approaches.

7.1 Search and Relative Thinking

We adapt the BSR model of relative thinking to our sequential search setup. According to this model, the decision-maker weights utility in the money and in the leisure dimension according to the variability of outcomes in these dimensions. Let her decision utility from purchasing the good at price p and spending L on search be given by

$$V^{rt}(p, L) = u - w_1(\Delta)p - w_2 L, \tag{18}$$

where the function $w_1(.)$ is the decision weight in the money dimension, Δ the price range, and the scalar w_2 is the weight in the leisure dimension; since there is no variation in this dimension in our setting, we just assume that weight equals some positive finite value. For our estimation, we normalize it to $w_2 = 1$. The price range Δ is given by the difference between the highest and lowest price, $\Delta = b - a$.

Since for a given range Δ the weighting function only scales prices, the optimal search strategy at constant search costs of c per search remains a reservation price policy. The reservation price is now implicitly defined by the indifference condition

$$c = \int_a^r w_1(\Delta)\,(r - p)\,f(p)dp. \tag{19}$$

With uniformly distributed prices, we obtain the decision-maker's search costs for a given reservation price r from the function

$$c(r) = \frac{w_1(\Delta)(r - a)^2}{2(b - a)}. \tag{20}$$

BSR assume that the weighting function $w_1(.)$ is a differentiable, decreasing function on $(0, \infty)$, and that $w_1(\Delta) \times \Delta$ is strictly increasing. While this leaves open various possible functional forms, BSR suggest the following functional form (see page 167 in Bushong et al. 2021) that we can use:

$$w_1(\Delta) = (1 - \rho) + \rho\frac{1}{\Delta + \xi}, \tag{21}$$

with $\rho \in [0, 1)$ and $\xi \in (0, \infty)$. For convenience, we call ρ the "degree of relative thinking." To obtain a functional form with only one free parameter we assume $\xi = 0$ (below, we also comment on the case with flexible ξ). For $\rho = 0$ we obtain the standard search cost model. For $\rho \to 1$, we obtain scale-independent search behavior.

7.2 Search Cost Estimates

We can jointly estimate search costs and the degree of relative thinking ρ using our ordered probit regression framework from Subsection 5.2. We only have to replace the search cost equation (12) by the new equation (20), and we take as given that the weighting function is given by equation (21). Column 1 of Table 9 shows the results from our ordered probit regressions with flexible ρ for both subject pools. For student subjects, we find a degree of relative thinking of $\rho = 0.89$ and average search costs per search of 0.08 Euros. The degree of relative thinking is significantly different from zero (p-value < 0.001). For AMT workers, the ordered probit regression generates a value of relative thinking slightly above one. Hence, we fix $\rho = 0.99$ and the obtain average search costs per search of 0.26 USD. The search cost estimates for the two subject pools therefore diverge from those of the model with diminishing sensitivity. Relative to the previous model, student subjects have lower and AMT workers higher estimated search costs. However, the estimates from both models have similar magnitudes.

In Column 2 of Table 5 we consider the results from the same regression where we additionally take into account our standard control variables. For student subjects, only gender is significant at the 10 percent level (coefficient = -0.05, se = 0.03). For AMT workers, we find that the dummy variables for above-median willingness to take risks (coefficient = 0.15, se = 0.05) and above-median CRT score (coefficient = -0.072, se = 0.04) are statistically significant. In a regression where ρ is explained by our standard controls, we do not see that any variable has a significant correlation with ρ. Taken together, these results are quite in line with those for the diminishing sensitivity model.

[Insert Table 9 and Table 10 about here]

We compare the estimated average search costs between treatments for given (estimated) values of ρ. Table 10 shows the results in Column 1 for student subjects and in Column 3 for AMT workers. In Columns 2 and 4, we again display the regression results from the standard model ($\rho = 0$). For student subjects, the average search costs per search vary between 0.08 Euros and 0.09 Euros. The differences are never significant (p-value > 0.748). For AMT workers, the average search costs per search vary between 0.21 USD and 0.29 USD. Again, these differences are never significant (p-value > 0.140). Finally, we derive for each searcher the individual expected search costs from the two smallest observed prices and the estimated search cost distribution. Figure 3 shows this distribution for student subjects and AMT workers. Most student subjects have expected search costs between zero and 0.10 Euro. For AMT workers, the distribution over expected search costs is more spread out on its support between zero and 0.50 USD.

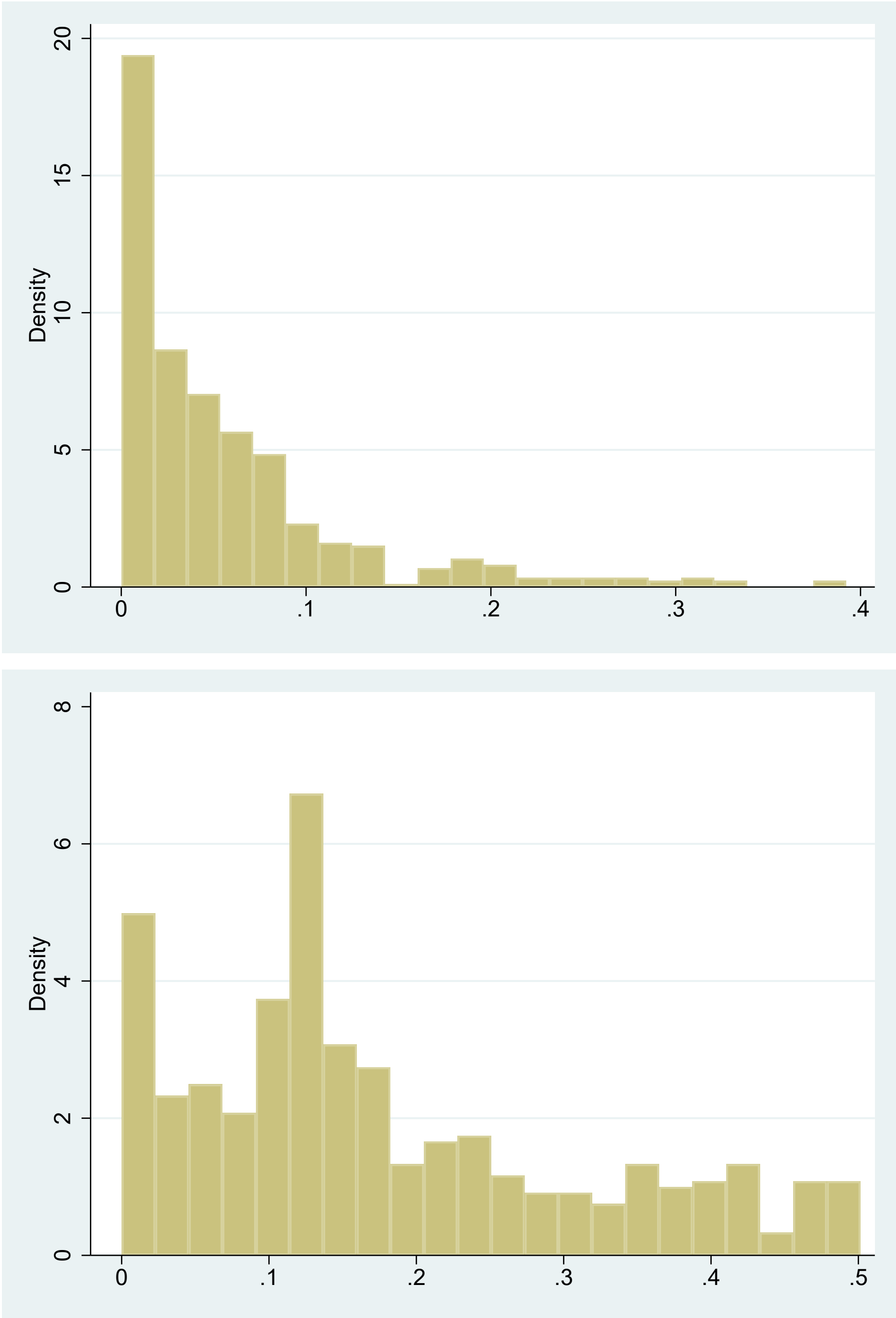

Figure 3: Distribution of expected individual search costs per search for student subjects (upper graph) and AMT workers (lower graph), for flexible degrees of relative thinking.

8 Conclusion

Search costs measure how easy it is for consumers to compare prices and to find the best product for their needs. Digital markets have the potential to make consumer search convenient and therefore to exert competitive pressure on firms. However, empirical search cost estimates for digital markets are typically large, which is often difficult to reconcile with searchers' labor supply choices. Why should the costs of finding a price quote online be several USD when the required effort only takes a few seconds and the searcher is willing to supply labor for a modest wage? To address this question, we conducted an online search experiment in which we can vary the price scale of a product without changing the effort required to obtain a price quote. The experimental setting allows us to abstract from product complexity and seller reputation. Moreover, we can fix subjects' beliefs about the price distribution at each shop. Even in this controlled environment we find that search cost estimates increase considerably in the price scale when we use a classic random sequential search model. In the highest price scale treatments, these estimates are unreasonably high.

To explain large search cost estimates that increase in the price scale, we proposed that individuals exhibit diminishing sensitivity: They tend to become less sensitive to fixed price variations when the price scale of the good increases. Therefore, they may undervalue the gains from search, in particular, when prices are high as in our high price scale treatments. Diminishing sensitivity is an important feature of several prominent preference models, and already has been suggested as a behavioral mechanism in the context of search more decades ago by Thaler (1980). We modified the random sequential search model so that it allows for diminishing sensitivity, and estimated both search costs and the degree of diminishing sensitivity with our experimental data. Taking into account diminishing sensitivity roughly equalizes the search cost estimates in our data. On average, student subjects require around 0.14 Euros for a 60 seconds investment into getting a price quote. Online workers at Amazon Mechanical Turk request a payment of 0.17 USD for the 85 seconds they need to find another price. Importantly, this estimate is consistent with the AMT workers' opportunity costs of time, which we infer from their average hourly earnings and their search duration.

Our results suggest that search cost estimates from observational data must be interpreted with caution as long as price scale effects are ignored. These estimates may not reflect the effort required to find price quotes or searchers' opportunity costs of time. Moreover, biased beliefs about the price distribution may further inflate search cost estimates. Our experimental paradigm provides a method to study these issues in future research.

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Table 1: Descriptive Statistics – Demographic Variables

	All Subjects	Searchers
	Panel A: Student Subjects	
Age	23.5 (3.2)	23.4 (3.0)
Gender (share females)	0.62	0.61
Willingness to take risk	5.4 (2.1)	5.4 (2.1)
CRT score	2.1 (1.1)	2.1 (1.1)
Study Field		
Economics	29.1%	30.0%
Law	5.7%	6.1%
Science	17.2%	16.7%
Humanities	22.6%	21.6%
Medical Science	15.3%	15.1%
Other	10.2%	10.4%
Observations	581	490
	Panel B: AMT Workers	
Age	39.6 (11.7)	39.9 (10.7)
Gender (share females)	0.44	0.45
Willingness to take risk	5.9 (2.7)	5.7 (2.7)
CRT score	1.7 (1.2)	1.8 (1.2)
Education		
No degree	0.3%	0.4%
Some high school	1.3%	1.5%
High school degree	24.3%	25.2%
Bachelor's degree	54.0%	52.3%
Master's degree or higher	20.1%	20.6%
AMT Labor		
Average hourly earnings	7.3 (7.6)	7.1 (6.7)
Average hours per week	20.8 (15.0)	20.1 (14.0)
Observations	626	528

Table 2: Descriptive Statistics – Search Behavior

	Price Scale	Share Searchers	Mean No. Searches if search	Median No. Searches if search	Gain Share if search
			Panel A: Student Subjects		
$S1.0$	[4.00, 8.00]	0.85	7.0 (6.6)	5	0.87
$S3.0$	[12.00, 24.00]	0.83	9.6 (15.1)	5	0.89
$S5.0$	[20.00, 40.00]	0.87	10.2 (12.1)	6	0.91
$S7.0$	[28.00, 54.00]	0.83	11.5 (17.2)	6	0.93
Observations		581	490	490	490
			Panel B: AMT Workers		
$S0.5$	[2.00, 4.00]	0.85	2.9 (4.1)	1	0.68
$S1.5$	[6.00, 12.00]	0.84	3.3 (9.0)	1	0.69
$S2.5$	[10.00, 20.00]	0.83	2.6 (3.3)	1	0.64
$S3.5$	[14.00, 28.00]	0.86	3.5 (6.8)	1	0.65
Observations		626	528	528	528

Table 3: Lower and Upper Bounds on Search Costs

	Price Scale	Mean Lower Bound Search Costs	Mean Upper Bound Search Costs
		Panel A: Student Subjects	
$S1.0$	[4.00, 8.00]	0.069 (0.143)	0.586 (0.676)
$S3.0$	[12.00, 24.00]	0.121 (0.209)	1.926 (2.323)
$S5.0$	[20.00, 40.00]	0.181 (0.396)	2.331 (3.434)
$S7.0$	[28.00, 54.00]	0.158 (0.444)	2.849 (4.324)
Observations		490	490
		Panel B: AMT Workers	
$S0.5$	[2.00, 4.00]	0.175 (0.249)	0.666 (0.398)
$S1.5$	[6.00, 12.00]	0.513 (0.722)	2.203 (1.091)
$S2.5$	[10.00, 20.00]	1.083 (1.316)	3.676 (1.894)
$S3.5$	[14.00, 28.00]	1.473 (1.958)	5.003 (2.692)
Observations		528	528

Table 4: Search Costs Estimates, $\gamma = 0$

	(1)	(2)	(3)
Panel A: Student Subjects			
$S1.0$		0.247***	0.379***
		(0.050)	(0.124)
$S3.0$		0.481***	0.731***
		(0.101)	(0.251)
$S5.0$		0.551***	0.846***
		(0.113)	(0.293)
$S7.0$		0.579***	0.872***
		(0.124)	(0.290)
Constant	0.458***		
	(0.066)		
Controls	No	No	Yes
σ	1.996***	1.826***	1.793***
	(0.502)	(0.447)	(0.439)
Observations	490	490	490
Panel B: AMT Workers			
$S0.5$		0.424***	0.449***
		(0.069)	(0.106)
$S1.5$		1.528***	1.564***
		(0.237)	(0.353)
$S2.5$		2.860***	2.816***
		(0.444)	(0.638)
$S3.5$		3.794***	3.702***
		(0.558)	(0.804)
Constant	2.296***		
	(0.270)		
Controls	No	No	Yes
σ	8.648***	4.486***	3.909***
	(1.779)	(0.739)	(0.633)
Observations	528	528	528

Notes: Ordered probit regressions with γ fixed at value zero. Standard errors are in parentheses. The controls are a dummy for above-median age, gender, a dummy for above-median willingness to take risk, and a dummy for above-median CRT score. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5: Search Costs and γ Estimates

	(1)	(2)	(3)	(4)
	Panel A: Student Subjects		*Panel B: AMT workers*	
Constant	0.138***	0.209**	0.171***	0.191***
	(0.050)	(0.092)	(0.040)	(0.054)
σ	0.542**	0.547**	0.370***	0.373***
	(0.229)	(0.229)	(0.104)	(0.103)
γ	0.415***	0.408***	0.975***	0.937***
	(0.120)	(0.119)	(0.089)	(0.089)
Controls	No	Yes	No	Yes
Observations	490	490	528	528

Notes: Ordered probit regressions with flexible γ. Standard errors are in parentheses. The controls are the same as in Table 4. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6: Search Costs Estimates, fixed γ

	(1)	(2)	(3)	(4)
	Panel A: Student Subjects		*Panel B: AMT Workers*	
	$\gamma = 0.415$:	$\gamma = 0$:	$\gamma = 0.975$:	$\gamma = 0$:
$S1.0/S0.5$	0.124***	0.247***	0.139***	0.424***
	(0.024)	(0.050)	(0.020)	(0.069)
$S3.0/S1.5$	0.155***	0.481***	0.169***	1.528***
	(0.032)	(0.101)	(0.023)	(0.237)
$S5.0/S2.5$	0.144***	0.551***	0.190***	2.860***
	(0.029)	(0.113)	(0.026)	(0.444)
$S7.0/S3.5$	0.133***	0.579***	0.183***	3.794***
	(0.028)	(0.124)	(0.024)	(0.558)
σ	0.541***	1.826***	0.364***	4.486***
	(0.128)	(0.447)	(0.052)	(0.739)
Observations	490	490	528	528

Notes: Ordered probit regressions with γ fixed at the estimated values from Table 5 and at zero. Standard errors are in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 7: Descriptive Statistics – Search Time

	Price Scale	Mean Search Duration	Median Search Duration	Mean Total Duration	Median Total Duration
		Panel A: Student Subjects			
$S1.0$	[4.00, 8.00]	62 (32)	55.5	464 (425)	358.5
$S3.0$	[12.00, 24.00]	65 (36)	53	520 (558)	382
$S5.0$	[20.00, 40.00]	62 (30)	55	658 (602)	561.5
$S7.0$	[28.00, 54.00]	60 (33)	54	758 (956)	455
Observations		487	490	469	490
		Panel B: AMT Workers			
$S0.5$	[2.00, 4.00]	89 (70)	64	274 (356)	177
$S1.5$	[6.00, 12.00]	84 (64)	68	249 (330)	150
$S2.5$	[10.00, 20.00]	86 (54)	73	281 (399)	161
$S3.5$	[14.00, 28.00]	81 (58)	66	299 (494)	167
Observations		516	528	503	528

Notes: Duration in seconds. For student subjects (AMT workers), the mean duration per search excludes 18 (26) searches that took longer than 10 minutes, and the mean total duration excludes 21 (25) searchers who took longer than 100 minutes.

Table 8: Alternative and Estimated Search Costs

	(1)	(2)
Estimated search costs	0.544*	0.418*
	(0.278)	(0.234)
Age		0.001
		(0.001)
Gender (share females)		-0.011
		(0.023)
Willingness to take risk		0.009**
		(0.004)
CRT score		-0.024**
		(0.010)
Constant	0.094***	0.076
	(0.025)	(0.050)
Observations	516	516
R^2	0.029	0.050

Notes: OLS regressions. The dependent variable is direct search costs. Robust standard errors are in parentheses. Missing observations are due to missing values for average hourly earnings. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 9: Search Costs and ρ Estimates

	(1)	(2)	(3)	(4)
	Panel A: Student Subjects		*Panel B: AMT workers*	
Constant	0.083***	0.127***	0.259***	0.263***
	(0.023)	(0.049)	(0.025)	(0.050)
σ	0.343***	0.344**	0.684***	0.611***
	(0.118)	(0.118)	(0.113)	(0.098)
ρ	0.894***	0.891***	0.999	0.999
	(0.048)	(0.049)		
Controls	No	Yes	No	Yes
Observations	490	490	528	528

Notes: Ordered probit regressions with flexible ρ. Standard errors are in parentheses. The controls are the same as in Table 4. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 10: Search Costs Estimates, fixed ρ

	(1)	(2)	(3)	(4)
	Panel A: Student Subjects		*Panel B: AMT Workers*	
	$\rho = 0.894$:	$\rho = 0$:	$\rho = 0.999$:	$\rho = 0$:
$S1.0/S0.5$	0.081***	0.247***	0.212***	0.424***
	(0.016)	(0.050)	(0.034)	(0.069)
$S3.0/S1.5$	0.087***	0.481***	0.256***	1.528***
	(0.018)	(0.101)	(0.040)	(0.237)
$S5.0/S2.5$	0.083***	0.551***	0.289***	2.860***
	(0.017)	(0.113)	(0.045)	(0.444)
$S7.0/S3.5$	0.080***	0.579***	0.275***	3.794***
	(0.017)	(0.124)	(0.040)	(0.558)
σ	0.343***	1.826***	0.670***	4.486***
	(0.084)	(0.447)	(0.111)	(0.739)
Observations	490	490	528	528

Notes: Ordered probit regressions with γ fixed at the estimated values from Table 9 and at zero. Standard errors are in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A Appendix

A.1 Instructions

This appendix shows the instructions to the experiment for the AMT workers. The prices mentioned in these instructions are for a hypothetical $S\,1.0$ treatment and change according to the treatment scale. The instructions for the student subjects are essentially the same and only differ in payment details.

Instructions for Part 2, Screen 1

The second part of the study is about buying a product. We call it "Product A."

Your budget for this product is 8 USD. If you buy product A at price P, then your earnings in the second part of the study will be 8 USD minus the price, that is 8 - P USD. The earnings from this part of the study will be paid as a bonus in MTurk.

You can simply buy product A for 8 USD. **You do not need to do anything else for this. All the earnings will be paid automatically.**

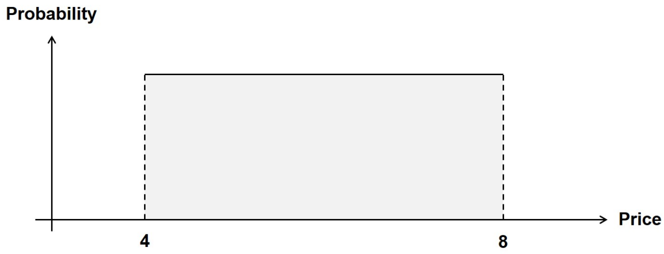
Alternatively, you can search for a lower price for product A in some online shops. On the next page we will explain how this works.

Instructions for Part 2, Screen 2

The second part of this study starts right after the first. However, you do not have to complete it immediately. We are going to send you an email message containing the link to the second part so that you can complete it anytime within the next four days.

In the second part of the study you will get access to up to 100 online shops that offer product A. The prices in each online shop vary between 4 and 8 USD. The following graph shows the probability distribution over all possible prices in each online shop. All prices between 4 and 8 USD are equally probable.

To find out the price of an online shop, a 16-digit code must be entered on the store page. This code will be given to you as soon as you click on an online shop (but it cannot be entered by "copy and paste"). After entering the code the price will be displayed.



To help you understand this principle, here is some typical code:

H2J2H34VSDF217GD

Please, enter this code on the next page! Note that "copy and paste" is not possible (just like at the actual online shops).

Instructions for Part 2, Screen 3

The code from the last page is: [Textfield]

Instructions for Part 2, Screen 4

Once you learn the price of product A at an online shop, you can decide whether you want to buy the product from that online shop or continue searching.

You can visit each online shop as often as you want. However, you can also stop at any time by clicking "Buy."

If you visit the shop again, you will not have to enter the code to find out the price (the price of an online shop does not change).

You can buy product A only once. As soon as you click "Buy", you purchase product A at the price of this online shop and the second part of this study is over.

Instructions for Part 2, Screen 5

If you do nothing, you automatically buy product A at a price of 8 USD. We then pay you a bonus of 8 - 8 = 0 USD for the second part of the study.

If you buy product A at price P in one of the online shops, we pay you a bonus of 8 - P USD.

If you visit some online shops but do not buy product A from any of them, you will automatically buy the product at the price of 8 USD and your bonus will be 8 - 8 = 0 USD.

Instructions for Part 2, Screen 6

Before continuing with the second part and searching for a price of product A, please enter the code [code] in MTurk now. This is necessary to end the first part and will secure your payment of 1 USD. Your earnings from the second part will be paid to you as a bonus and there will be no need to enter anything else in MTurk to end the second part.

You can also continue searching at some later time. We are going to send you an email with the link to the second part. You have four days to buy product A. Of course, participation in the second part is completely optional. However, you will not receive a bonus payment if you decide not to search.

I have entered the code [code] in MTurk [Checkbox]

We will not be able to pay you if you do not enter this code in MTurk!

Please follow this link to the second part: [Link]

A.2 Expected Individual Search Costs

In our ordered probit model from Subsection 5.2, we assume that the log of search costs, $\ln c$, is normally distributed. The probability density function and cumulated distribution function of $\ln c$ are given by

$$\phi\left(\frac{\ln c - x\beta}{\sigma}\right) \text{ and } \Phi\left(\frac{\ln c - x\beta}{\sigma}\right), \tag{22}$$

where ϕ and Φ are the standard normal density and distribution functions. The corresponding probability density function and cumulated distribution function of c equal

$$\phi\left(\frac{\ln c - x\beta}{\sigma}\right)\frac{1}{c} \text{ and } \Phi\left(\frac{\ln c - x\beta}{\sigma}\right). \tag{23}$$

The (unconditional) expected value of search costs equals

$$\mathbb{E}[c] = \exp\left(x\beta + \frac{\sigma^2}{2}\right). \tag{24}$$

On the individual level, we are interested in the conditional expected value of search costs given $c(p^1) \leq c < c(p^2)$, i.e., conditional on the lowest and second lowest price an individual has observed and the implied lower and upper bound on search costs. This conditional expectation is given by

$$\mathbb{E}[c \mid c(p^1) \leq c < c(p^2)] \quad = \quad \int_{c(p^1)}^{c(p^2)} \frac{c\phi\left(\frac{\ln c - x\beta}{\sigma}\right)\frac{1}{c}}{\Phi\left(\frac{\ln c(p^2) - x\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p^1) - x\beta}{\sigma}\right)} dc. \tag{25}$$

This integral has a closed-form solution, so we obtain

$$\mathbb{E}[c \mid c(p^1) \leq c < c(p^2)] = \mathbb{E}[c] \cdot \frac{\Phi\left(\frac{\ln c(p^2) - (x\beta + \sigma^2)}{\sigma}\right) - \Phi\left(\frac{\ln c(p^1) - (x\beta + \sigma^2)}{\sigma}\right)}{\Phi\left(\frac{\ln c(p^2) - x\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p^1) - x\beta}{\sigma}\right)}. \tag{26}$$

A.3 Additional Tables

Table A1: Descriptive Statistics Across Treatments, all subjects

Treatment	$S\,1.0/S\,0.5$	$S\,3.0/S\,1.5$	$S\,5.0/S\,2.5$	$S\,7.0/S\,3.5$	One-way ANOVA p-value
		Panel A: Student Subjects			
Age	23.3 (3.0)	23.7 (3.2)	23.4 (3.0)	23.5 (3.6)	0.716
Gender (share females)	0.65	0.59	0.64	0.60	0.626
Willingness to take risk	5.5 (2.3)	5.7 (2.1)	5.4 (2.1)	5.2 (2.2)	0.209
CRT score	2.0 (1.1)	2.1 (1.1)	2.1 (1.1)	2.1 (1.1)	0.997
Observations	148	146	143	144	
		Panel B: AMT Workers			
Age	40.5 (11.7)	39.4 (11.2)	40.2 (12.8)	38.7 (11.2)	0.522
Gender (share females)	0.48	0.44	0.44	0.40	0.597
Willingness to take risk	5.8 (2.8)	5.8 (2.7)	6.1 (2.7)	5.8 (2.7)	0.747
CRT score	1.7 (1.2)	1.8 (1.2)	1.5 (1.3)	1.7 (1.2)	0.148
Education	2.9 (0.8)	2.9 (0.7)	3.0 (0.7)	2.9 (0.7)	0.350
Average hourly earnings	7.0 (8.2)	7.5 (7.7)	8.3 (9.4)	6.4 (4.3)	0.147
Average hours per week	20.9 (15.0)	22.0 (14.3)	19.5 (14.5)	20.7 (16.1)	0.545
Observations	140	161	153	172	

Notes: Age is in years, willingness to take risk is on a scale from 0 (not willing to take risk at all) to 10 (very willing to take risk), CRT score is on a scale from 0 to 3, education is 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), average hourly earnings is in USD.

Table A2: Descriptive Statistics Across Treatments, searchers only

Treatment	$S1.0/S0.5$	$S3.0/S1.5$	$S5.0/S2.5$	$S7.0/S3.5$	One-way ANOVA p-value
			Panel A: Student Subjects		
Age	23.4 (3.1)	23.5 (2.9)	23.5 (3.2)	23.2 (2.9)	0.887
Gender (share females)	0.63	0.60	0.65	0.56	0.536
Willingness to take risk	5.5 (2.2)	5.7 (2.0)	5.3 (2.1)	5.2 (2.2)	0.380
CRT score	2.1 (1.1)	2.0 (1.1)	2.1 (1.0)	2.1 (1.1)	0.966
Economics	0.30	0.29	0.24	0.33	0.398
Observations	126	121	124	119	
			Panel B: AMT Workers		
Age	41.3 (11.9)	40.0 (11.3)	40.3 (12.7)	38.6 (10.7)	0.296
Gender (share females)	0.50	0.41	0.46	0.41	0.365
Willingness to take risk	5.6 (2.9)	5.5 (2.6)	6.0 (2.6)	5.7 (2.6)	0.500
CRT score	1.8 (1.2)	1.9 (1.2)	1.6 (1.3)	1.8 (1.2)	0.119
Education	2.9 (0.8)	2.9 (0.7)	3.0 (0.8)	2.9 (0.7)	0.546
Average hourly earnings	7.1 (7.9)	7.1 (5.5)	8.2 (8.7)	6.3 (4.2)	0.138
Average hours per week	20.6 (14.4)	20.8 (12.8)	18.8 (13.5)	20.1 (15.3)	0.655
Observations	119	135	127	147	

Notes: Age is in years, willingness to take risk is on a scale from 0 (not willing to take risk at all) to 10 (very willing to take risk), CRT score is on a scale from 0 to 3, education is 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), average hourly earnings is in USD.

Table A3: Search and Recall

Number Searches	Observations	Share	Share Last Shop	Av. Probability of Recall
		Panel A: Student Subjects		
1	61	12.4%	100%	0%
2	66	13.5%	83.3%	16.7%
3	38	7.8%	73.7%	13.2%
4	28	5.7%	53.6%	15.5%
5	44	9.0%	56.8%	10.8%
6	32	6.5%	31.3%	13.8%
7	31	6.3%	61.3%	6.5%
8	17	3.5%	47.1%	7.6%
9	9	1.8%	55.6%	5.6%
10	35	7.1%	37.1%	7.0%
11–20	88	18.0%	39.8%	4.3%
>20	41	8.4%	26.8%	1.8%
		Panel B: AMT Workers		
1	304	57.6%	100%	0%
2	69	13.1%	89.9%	10.1%
3	49	9.3%	73.5%	13.3%
4	22	4.2%	63.6%	12.1%
5	23	4.4%	65.2%	8.7%
6	13	2.5%	53.8%	9.2%
7	11	2.1%	45.5%	9.1%
8	6	1.1%	66.7%	4.8%
9	–	–	–	–
10	8	1.5%	37.5%	6.9%
11–20	14	2.7%	64.3%	2.6%
>20	9	1.7%	44.4%	2.2%

Notes: The average probability of recall is defined as the average probability with which a particular previously sampled shop is recalled provided that the subject does buy from the last sampled shop. Formally, it is defined by (1 − share last shop)/(number searches − 1).

Table A4: Price Dependence of Search, Student Subjects

	Searching more than once		Continue search	
	(1)	(2)	(3)	(4)
Price in Shop 1	0.0218***	0.0957***		
	(0.000)	(0.000)		
Price in current shop			0.0112***	0.0740***
			(0.000)	(0.000)
$S3.0$	-0.319***	-0.456*	-0.0940***	0.157
	(0.000)	(0.061)	(0.000)	(0.193)
$S5.0$	-0.532***	-0.0716	-0.222***	0.108
	(0.000)	(0.762)	(0.000)	(0.306)
$S7.0$	-0.735***	0.0394	-0.346***	0.151
	(0.000)	(0.870)	(0.000)	(0.175)
$S3.0 \times$ Price		-0.0421*		-0.0555***
		(0.098)		(0.000)
$S5.0 \times$ Price		-0.0747***		-0.0610***
		(0.002)		(0.000)
$S7.0 \times$ Price		-0.0821***		-0.0655***
		(0.001)		(0.000)
Constant	0.752***	0.315*	0.789***	0.408***
	(0.000)	(0.057)	(0.000)	(0.000)
Observations	490	490	4666	4666

Notes: OLS regressions. Robust standard errors are in parentheses. The dependent variable in Columns (1) and (2) has value 1 if subjects searched more than one shop and value 0 if subjects searched exactly one shop. The dependent variable in Columns (3) and (4) has value 1 if subjects continued searching after observing the price in the current shop and value 0 otherwise. Clustering at the individual level in Columns (3) and (4). Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A5: Price Dependence of Search, AMT Workers

	Searching more than once		Continue search	
	(1)	(2)	(3)	(4)
Price in Shop 1	0.0432***	0.258***		
	(0.000)	(0.000)		
Price in current Shop			0.0443***	0.231***
			(0.000)	(0.000)
S1.5	-0.320***	-0.323	-0.220**	0.0200
	(0.000)	(0.239)	(0.024)	(0.950)
S2.5	-0.613***	0.106	-0.577***	-0.124
	(0.000)	(0.730)	(0.000)	(0.575)
S3.5	-0.860***	0.0989	-0.764***	0.0150
	(0.000)	(0.732)	(0.000)	(0.947)
S1.5 x Price		-0.142*		-0.151***
		(0.060)		(0.003)
S2.5 x Price		-0.219***		-0.180***
		(0.003)		(0.000)
S3.5 x Price		-0.229***		-0.197***
		(0.002)		(0.000)
Constant	0.349***	-0.297	0.520***	-0.0354
	(0.000)	(0.171)	(0.000)	(0.827)
Observations	528	528	1628	1628

Notes: OLS regressions. Robust standard errors are in parentheses. The dependent variable in Columns (1) and (2) has value 1 if subjects searched more than one shop and value 0 if subjects searched exactly one shop. The dependent variable in Columns (3) and (4) has value 1 if subjects continued searching after observing the price in the current shop and value 0 otherwise. Clustering at the individual level in Columns (3) and (4). Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.