Search Costs and Context Effects*

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Abstract

Empirical search cost estimates are often large and increasing in the size of the transaction, even if search can be done conveniently online. To assess this pattern systematically, we conduct an online search experiment in which we manipulate the price scale while keeping the physical search effort for each price quote constant. We also record the time subjects need to obtain a price quote in order to derive a direct measure of subjects' time and hassle costs of search. Based on a standard search model, we confirm that search cost estimates are large relative to directly elicited search costs and increasing in the price scale. We then modify the search model to allow for context effects, i.e., the tendency that people become less sensitive to price variations of fixed size when the price scale or range of outcomes increases. With the modified model, we find scale-independent search cost estimates that correspond well to subjects' directly elicited search costs. We show that the consumer welfare losses from context effects can be quite substantial and discuss how empirical work could deal with scale-effects.

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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 overview article 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 simple.[1] Gorodnichenko et al. (2018) find in a large dataset of online price postings from many consumer markets that the ratio between the highest and the lowest price of a product is on average 1.65 in the United States and 1.52 in the United Kingdom, even after accounting for seller activity. Further, a large literature estimates consumer search costs from observational data in various digital markets. It consistently makes two observations: First, the estimated search costs are typically fairly large, despite the convenience of the online setting.[2] Second, they are increasing in the price scale of the product category. To illustrate these observations, we list the estimated search costs from three different online product markets:

Study	Product, Search Environment	Average Prices	Av. Estimated Search Costs (per search)
De los Santos et al. (2012)	Books, Online Book Stores	8 – 23 USD	1.35 USD
Moraga-González et al. (2013)	Computer Memory Chips, Price Comparison Sites	116 – 182 USD	8.70 USD
Giulietti et al. (2014)	Electricity Contracts, Internet Search	≈ 592 USD	> 47.30 USD

For comparison, the median hourly wage in the US in the decade from 2001 to 2010 was between 10.19 and 12.50 USD. Judging by these numbers, it appears as if searching prices on price comparison websites is not much different from searching at brick-and-mortar stores that

[1] See, e.g., Brynjolfsson and Smith (2000), Baye et al. (2004), Orlov (2011), and Einav et al. (2015).

[2] Large average search costs are found in digital markets for books (Hong and Shum 2006, De los Santos et al. 2012), memory chips (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).

are located significant commutes away from each other.[3]

Several reasons could justify why search cost estimates are large and increasing in the price scale of the product category. Consumers may be pessimistic about the benefits from search and therefore spend too little effort on finding the best deal. More valuable products are typically also more complex and may require more time to inspect. Alternatively, larger purchases may involve trust issues so that some consumers hesitate to choose an option even if it is cheaper and, on paper, offers the same quality and services. However, it is not clear whether these reasons or some other – potentially behavioral – mechanisms cause large search costs that increase in the price scale.

To study this pattern systematically, we conduct an online search experiment with two crucial features: First, we precisely measure the time subjects need to identify a price quote in our search environment. Hence, we can compare the estimated search costs with subjects' opportunity costs of time to evaluate whether they are too large, too small, or just about right. Second, we vary the price scale while keeping physical search costs constant. A higher price scale implies larger potential savings and hence increased benefits from search. This treatment variation allows us to detect whether the search cost estimates from a standard search model mechanically increase in the price scale of the product category. The advantage of the experimental setting is that we can rule out the traditional explanations for large and scale-dependent search costs mentioned above: Subjects are informed about the potential gains from search, the complexity of the product and the search process are kept constant, and trust issues do not arise.

In the experiment, subjects can search for the lowest price of a (hypothetical) homogeneous product in up to 100 online shops. To identify a price quote at an online shop, they have to enter a 16-digit code, which takes roughly around a minute. Subjects' payoff in the experiment equals the price savings they realize. They can take as much time for search as they want and they even can have breaks in between searches. The price distribution is exogenously given, identical, and independent for each shop. Our treatment variation is the price scale. In the lowest scale treatment, prices are distributed uniformly on the interval $[\alpha,\beta]$, while in the highest scale treatment, prices are distributed uniformly on the interval $[7\alpha, 7\beta]$. We conduct the experiment with two fairly different subject pools, online workers on Amazon Mechanical Turk (AMT) and student subjects. For both subject pools, we elicit estimates of their opportunity costs of time, which we use to evaluate the size of estimated search costs.

[3]Indeed, Cavallo (2017) finds that online and offline prices of multi-channel retailers are similar, both in their level and their adjustment frequency. Gorodnichenko et al. (2018) find that online prices are changed more frequently than offline prices, but that the duration of online price spells is still large. Relatedly, the literature also documents large switching costs; see, Karle et al. (2022) for an overview. For example, Hortaçsu et al. (2017) report that by investing 15 minutes into finding a cheaper energy provider, consumers could reduce their annual electricity costs by 100 USD.

Our experimental setting closely resembles the framework of the random sequential search model (e.g., McCall 1970, Stahl 1989). We therefore use this model to estimate search costs. It implies that a subject's reservation price lies between the lowest and second lowest discovered price. This gives rise to an ordered probit framework, which allows us to estimate the distribution of search costs. Indeed, we find large search costs that increase in the price scale. Taking into account subjects' opportunity costs of time and the time they need to find price quotes in our setting, search costs per search should be at the order of 0.20 USD (Euro) in each treatment. However, in the highest scale treatments, search costs per search are 3.79 USD for AMT workers and 0.58 Euro for student subjects. Between the lowest and the highest scale treatments, search costs increase by 795 percent for AMT workers and by 134 percent for student subjects. We find similar results in a number of robustness checks, including one in which subjects search for the lowest prices of two products from different price scales.

With these results we replicate, for two different subject groups, the findings from the empirical literature in a setting where product complexity, consumer beliefs, and trust issues do not provide an explanation. This indicates that the standard random sequential search model most likely does not adequately capture subjects' time and hassle costs of search and that it needs to be updated to mitigate the apparent contradictions.

To avoid search cost estimates that increase in the price scale, we next allow for context effects in our search model. A context effect arises if the price scale or the range of outcomes affects the decision-maker's valuation of potential monetary gains relative to the costs of realizing these gains. A first context effect that could matter in our setting is *diminishing sensitivity*: It implies that a certain amount of price savings appears large to a decision-maker when the price scale is small, but small when the price scale is large. Diminishing sensitivity is a feature of prospect theory and has been used to explain the famous jacket-calculator vignette[4]; see Thaler (1980), Tversky and Kahneman (1981), Azar (2011), and Shah et al. (2015). A second relevant context effect in our setting is *relative thinking* (Bushong et al. 2021): Relative thinking implies that the decision-maker becomes less sensitive to fixed price variations as the range of potential outcomes gets large. Both diminishing sensitivity and relative thinking have the same impact on search incentives: As prices and the price range increase, the perceived benefits from saving a given amount become small relative to the physical costs of realizing

[4]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. However, the jacket-calculator vignette does not suggest an experimental design that allows to estimate search costs. We therefore consider a generic search setting.

these savings. For each context effect, we integrate an established parametrization from the literature in the empirical search model. The scale variation in our experiment then allows us to jointly estimate search costs and the level of context effects. The two parametrizations generate very similar results, so we consider both of them throughout the paper.[5]

We find that taking into account context effects roughly equalizes the search cost estimates in all treatments. Moreover, it also almost equalizes the search costs of AMT workers and student subjects. Under the diminishing sensitivity parametrization, average search costs per search are 0.17 USD for AMT workers and 0.14 Euro for student subjects; under the relative thinking parametrization, these values are 0.20 USD and 0.14 Euro, respectively. Importantly, these search cost estimates are fairly close to the model-free opportunity costs of time which we obtain from subjects' search time. We therefore conclude that context effects can be an important driver of search cost estimates: When we compare the search cost estimates between the original and the modified models, we find for AMT workers that in the highest scale treatment 95 percent of the original search cost estimate are due to context effects, not due to time and hassle cost of search; for student subjects, this share is 77 percent.

Using the updated search model and our search cost estimates, we can assess subjects' welfare loss that is due to context effects. If an individual searches less, she economizes on search costs, but pays a higher price in expectation. We find that the welfare loss from context effects is relatively modest for intermediate degrees of diminishing sensitivity (or relative thinking). However, for large context effects (as for the AMT workers), the welfare loss can be substantial, up to 40 percent of the total gains from search. In particular, we find that the welfare losses from context effects are large for individuals with relatively high search costs.

Related Literature. The paper contributes to a growing literature that estimates physical search costs using the classic search models from the industrial organization literature (e.g., Burdett and Judd 1983, Stahl 1989). This literature was initiated by Hortaçsu and Syverson (2004) and Hong and Shum (2006), and it uses observational data. Important contributions on price search in online settings include De los Santos et al. (2012), Moraga-González et al. (2013), Giulietti et al. (2014), Honka (2014), Koulayev (2014), De los Santos (2018), 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 obtain a price quote. We can therefore 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. In addition, from subjects'

[5]In Section 7, we briefly describe how diminishing sensitivity and relative thinking can be disentangled in future research.

opportunity costs of time and the time they need to identify a price quote, we can derive a direct search cost measure to which we can compare our search cost estimates.

There is also an experimental literature on consumer search and search markets; see, e.g., Kogut (1990), Sonnemans (1998), Schunk and Winter (2009), Brown et al. (2011), and Casner (2021) 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. To the best of our knowledge, this is the first experimental paper that considers "real" time and hassle costs as subjects need to insert a 16-digit code for each price quote. This allows us to study how the relationship between physical search costs and monetary gains from 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 close to a generic online search environment. This is different from real-effort tasks where subjects need to complete an assignment within a narrow time-frame (as, for example, in DellaVigna and Pope 2018).

On a more general level, the paper is related to the literature on context effects, see, e.g., Azar (2007), Bordalo et al. (2012, 2013), Kőszegi and Szeidl (2013), Gabaix (2014), Dertwinkel-Kalt et al. (2017), and Bushong et al. (2021). Context effects occur if changes in the choice set affect the preference order over a given set of options. We examine context effects in a search environment and their implications for empirical search cost estimates. Our results are consistent with diminishing sensitivity and relative thinking (Bushong et al. 2021).

The rest of the paper is organized as follows. In Section 2, we describe the random sequential search model and modify it by allowing for context effects. In Section 3, we describe our experimental design. In Section 4, we characterize our subject pool and average search behavior. In Section 5, we estimate search costs in our online setting and the level of context effects. Moreover, we assess the welfare consequences of context effects in a search environment. In Section 6, we present a number of robustness checks and extensions. Section 7 concludes and outlines the implications of our findings for empirical work on search costs. The instructions for the experiment as well as a number of additional analyses are relegated to the appendix.

2 Search and Context Effects

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

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

This shape of the indirect utility function originates from the standard utility framework 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.[6] There is a (large) finite number of firms that offer the good at varying prices. Each firm chooses its price p according to the continuously differentiable 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. Search costs are constant so that we can write $L = nc$, where n is the number of searches and c is the cost per search, i.e., the required time to get a price quote times the opportunity costs of time. After each search, the decision-maker chooses whether to purchase the good at the lowest price discovered so far or to conduct one more search. The 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

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

Intuitively, the reservation price r is such that the expected price savings are equal to the marginal cost c of one more search. 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. Note that higher search costs c are associated to a higher reservation price r. We can calculate the value of the indirect utility function (1) at the optimal search strategy as

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

[6]The 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 suppose 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 then 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 $u_1(y, 1)$ 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. Following the literature, we normalize $u_1(y, 1) = 1$.

where r is defined in equation (2). The value in (3) is the expected payoff from following an optimal reservation price policy. The last term in this expression captures the expected number of searches multiplied by search costs.

Before we introduce context effects, we briefly comment on two assumptions in this search model that are empirically relevant. First, our search paradigm is random sequential search, which is a classic search paradigm in the literature. There is, however, an alternative search paradigm that is also frequently considered in the theoretical and empirical literature, i.e., non-sequential search (or "fixed sample size search") as introduced by Burdett and Judd (1983). Non-sequential search means that the decision-maker chooses the number of price quotes 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 (from an ex-ante perspective) the sum of search costs and expected purchase price. In Section 4, we comment on whether sequential or non-sequential search better captures search behavior in our experiment, and Appendix A.3 contains a detailed analysis of this issue.

The second assumption we are making is that search costs are constant in the number of searches. This assumption is plausible as long as the total time spent on search is small relative to the total available time and it is possible to have breaks in between searches. Otherwise, extended search activity may result in fatigue so that search costs are convex. In Section 6, we discuss to what extent convex search costs can explain search behavior in our setting.

2.2 Context Effects

We now allow for context effects. In particular, we show that context effects can lead to increasing reservation prices, and hence to inflated search cost estimates in empirical work when they are not taken into account. When searching, the perceived benefits of search may depend on the price scale or the range of possible outcomes. Following the literature on behavioral welfare analysis (e.g., Bernheim and Taubinsky 2018), we capture context effects in an indirect utility function that represents decision-utility, while experienced utility is again given by equation (1). The decision-maker's decision utility is given by

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

so that the indifference condition in equation (2) which defines the reservation price r becomes

$$c = \int_a^r (v(r, F) - v(p, F))\, f(p) dp. \tag{5}$$

The function v may represent diminishing sensitivity as in prospect theory. It is then an increasing and concave function of the price and independent of the distribution F. Intuitively, diminishing sensitivity describes the decision-maker's tendency to become less sensitive towards price variations of fixed size as the price level increases. Alternatively, the function v may capture context-dependent preferences like relative thinking as defined by Bushong et al. (2021). It then depends on the range of outcomes defined by the distribution F, which in our case is given by the value $\Delta_F = b - a$. Intuitively, if the decision-maker is subject to relative thinking, she is less sensitive to fixed price variations when the variability of outcomes Δ_F is large. To formalize the shape of v, we adopt the following functional forms:

$$\text{diminishing sensitivity:} \quad v^{ds}(p, F) = \frac{p^{1-\gamma}}{1-\gamma},$$
$$\text{relative thinking:} \quad v^{rt}(p, F) = \frac{1}{\Delta_F^{\rho}} p.$$

We call γ the degree of diminishing sensitivity and ρ the degree of relative thinking; v^{ds} is the power function[7] and v^{rt} a function that Somerville (2022) uses to estimate the degree of relative thinking in an experimental setting.[8] In our search context, the two functions share several features. Both functions collapse to the standard case $v(p, F) = p$ if the functional parameters γ, ρ equal zero. Moreover, both models imply *scale-independent search behavior* if the functional parameters equal one. To see this, define by $z > 1$ a parameter that scales all prices that the decision-maker may observe, i.e., the support $[a, b]$ becomes $[za, zb]$ and the distribution becomes $F(zp) = F(p)$ for each $p \in [a, b]$. Note that for $\gamma = 1$ we have $v^{ds}(p, F) = \ln(p)$. If $\gamma = 1$ and $\rho = 1$, we get

$$v^{ds}(zr, F) - v^{ds}(zp, F) = v^{ds}(r, F) - v^{ds}(p, F), \tag{6}$$
$$v^{rt}(zr, F) - v^{rt}(zp, F) = v^{rt}(r, F) - v^{rt}(p, F), \tag{7}$$

and hence the same search effort under any scale. A (hypothetical) empirical researcher who observes the decision-maker's reservation prices at varying scales, but does not take into account context effects, would then conclude that search costs are increasing in the price scale.

[7]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 only for tractability reasons. Specifically, we point out that diminishing sensitivity is different from diminishing utility from money. The latter matters only for large changes in wealth, see Rabin's calibration theorem (Rabin 2000).

[8]Somerville (2022) conducts experiments in which he tests Bushong et al. (2021) relative thinking against focusing as defined by Kőszegi and Szeidl (2013) in a setting with decoy effects. He finds evidence mostly in favor of relative thinking. Here we use a slightly different notation to differentiate relative thinking from diminishing sensitivity and we allow for a broader range of values of the relative thinking parameter.

The same holds for all degrees of diminishing sensitivity $\gamma > 0$ and relative thinking $\rho > 0$, respectively.

To describe these observations formally, we introduce the following notation. Denote by r_γ (r_ρ) the reservation price at search costs c and distribution of prices F on the interval $[a, b]$ when the decision-maker exhibits the degree of diminishing sensitivity γ (relative thinking ρ). It is defined by equation (5), after substituting function v^{ds} (function v^{rt}). We are interested in how this value changes when prices are scaled by a factor z. Denote by $r_\gamma(z)$ and $r_\rho(z)$ the corresponding reservation prices. The values $\frac{r_\gamma(z)}{z}$ and $\frac{r_\rho(z)}{z}$ are relative reservation prices. If a relative reservation price decreases in z this means that the decision-maker conducts, in expectation, more searches when the price scale increases. We obtain the following results (their proof is in Appendix A.1).

Proposition 1 (Reservation Prices and Context Effects). *Let the distribution F over prices on the interval $[a, b]$ be given. Consider a decision-maker with positive search costs c. If she exhibits diminishing sensitivity of degree γ and c is small enough such that her reservation price is smaller than b at all values $\gamma \in [0, 1]$, then the following statements hold.*

(i) If $\gamma = 1$ ($\gamma < 1$), the relative reservation price $\frac{r_\gamma(z)}{z}$ is constant (strictly decreasing) in z. This means that the expected number of searches remains the same (increases) if prices are scaled up by a factor $z > 1$.

(ii) The value $\frac{\partial}{\partial z}\left[\frac{r_\gamma(z)}{z}\right]$ strictly increases in γ. This means that the extent to which the expected number of searches increases in z is reduced as the degree of diminishing sensitivity increases.

The same statements hold for the relative reservation price $\frac{r_\rho(z)}{z}$ if the decision-maker exhibits relative thinking of degree ρ and c is small enough such that her reservation price is smaller than b at all values $\rho \in [0, 1]$.

3 Experimental Design and Procedures

The goal of our experiment is three-fold. First, we want to test whether a scale variation in prices drives up estimated search costs when the empirical search model does not take context effects into account. Second, we wish to compare estimated search costs to a direct search cost measure that is derived from subjects' opportunity cost of time. Third, we want to identify the level of context effects that keeps estimated search costs constant for varying price scales.

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.2. Part 2 takes place after the completion of Part 1.

In Part 2, subjects have to purchase a hypothetical product[9], 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. Providing this discretion is essential for the experiment, otherwise we would measure search costs at a particular point in time and not general search costs.

The treatment variation is the price scale of the 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 have $\alpha = 4$ and $\beta = 8$ (Euro or USD, depending on the subject pool). In scale treatment Sz for some $z > 0$, we have $a = z\alpha$ and $b = z\beta$. 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. Copy-and-paste is disabled 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 shop's price. They can then choose whether to purchase the product at this shop, to purchase it at a previously searched shop, or to continue search. They can access all previously searched shops from an overview page 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.

We conduct the experiment with two subject pools, online workers at Amazon Mechanical Turk and student subjects.[10] The situation of these two subject groups is fairly different. The AMT workers in our sample spend considerable time on the platform – around 20 hours per week – in order to earn an additional income. Student subjects occasionally participate in economic experiments. When we conducted the experiment with them, the university was still in lockdown mode, so student subjects arguably had a lot of time at their disposal. Before starting the experiment, we registered it on aspredicted.org (registry number #68519) and obtained

[9]Using a hypothetical product instead of a real product has a crucial advantage for the interpretation of the experimental data. If subjects would buy a real product, the price scale could be interpreted as a signal about its value, which potentially could influence search behavior.

[10]We do this in order to address potential concerns whether the results from one subject pool are also valid for other subjects (see, e.g., Snowberg and Yariv 2021).

IRB approval from the Board for Ethical Questions in Science of the University of Innsbruck.

AMT Workers. Our first set of subjects are online workers on AMT. We implemented four scale treatments with $z \in \{0.5, 1.5, 2.5, 3.5\}$ and call these treatments $S0.5$, $S1.5$, $S2.5$, and $S3.5$, respectively. The currency of prices and payoffs for 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.[11] 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 $S3.5$. All of them were located in the United States, had a HIT (human intelligence task) approval rate above 98 percent, and more than 500 approved HITs.

Student Subjects. Our second set of subjects are students from the University of Innsbruck. For recruitment we used the software hroot (Bock et al. 2014). We implemented four scale treatments with $z \in \{1.0, 3.0, 5.0, 7.0\}$. 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 Euro. The participation fee for the completion of the first part was 5 Euro. 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.

At the start of the instructions, we clearly state that it is an experiment conducted by researchers from the University of Innsbruck, Frankfurt School of Finance and Management, and KU Leuven. To avoid selection into the second part based on treatment, the price scales must be chosen so that starting search is attractive even in the lowest price scales. In our setup, commencing search and identifying one price quote does not take more than three minutes. The expected payoff of this operation is one USD for AMT workers in treatment $S0.5$ and two Euro for student subjects in treatment $S1.0$, respectively, so we think that our design choices meet this criterion. Indeed, the same share of subjects starts searching in all treatments (see Subsection 4.2 for details). The potential payoffs for subjects in the highest scale treatments are clearly substantial, especially for AMT workers. However, lotteries that pay similar amounts with positive probability have been implemented on AMT (e.g., DellaVigna and Pope 2018, Ronayne et al. 2021).

[11] 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.

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 AMT workers and student subjects. In Subsection 4.2, we examine some basic statistics on search effort and search time in our experiment and we discuss to what extent subjects' search behavior is in line with sequential search.

4.1 Descriptive Statistics

Table 1 provides an overview of the demographic variables of our 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." Since our model is only applicable to subjects who conduct at least one search, we will focus on the searchers in much of our empirical analysis.

Overall, 84.3 percent of all AMT workers and also 84.3 percent of all student subjects in our sample are searchers.[12] 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 or a higher degree. There are no significant differences in these demographic variables between searchers and non-searchers. The student 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. Again, there are no significant differences in personal characteristics between searchers and non-searchers.

For both AMT workers and student subjects we elicit the general willingness to take risk (as measured by Dohmen et al. 2011) and cognitive ability through a cognitive reflection test (CRT). The willingness to take risk 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. AMT workers' average willingness to take risks is 5.9, for student subjects this value is 5.4. The average CRT-score of both groups is also rather similar, 1.7 for AMT workers and 2.1 for student subjects (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).

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

Table 1: Descriptive Statistics – Demographic Variables

	All Subjects	Searchers
	Panel A: AMT Workers	
Age	39.6 (11.7)	39.9 (11.6)
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
	Panel B: 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

We ask 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 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). For our student subjects we know that they earn on average 15 Euro per hour at the experimental laboratory of the University of Innsbruck. This number is also published on the website of Innsbruck EconLab. On average, our subjects participated in 4.3 (sd = 4.8) experiments at this laboratory so far.

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 A6 and A7 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 the samples of searchers are balanced between treatments.

4.2 Search Behavior, Search Time, and Search Paradigm

We provide an overview of search behavior and search time in our experiment. Moreover, we briefly discuss to what extent search behavior conforms to the sequential and non-sequential search paradigm. Table 2 shows in the upper two panels 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 by searchers, that is, the value $(b - \bar{p})/(b - a)$ where $\bar{p}$ is the average price paid by searchers. The lower two panels of Table 2 display subjects' "mean search duration" and "mean total duration" as well as the corresponding median values. The mean search duration is the average time (in seconds) it takes a subject from entering an online shop to discovering the price at this shop. This is roughly the time a subject needs to record the 16-digit code and to insert it on the next page. The mean total duration is the time (in seconds) between entering the overview page and buying the hypothetical product.

Average Search Behavior. Among AMT workers, the share of searchers 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 $S3.5$. However, this difference is only borderline statistically significant (Jonckheere-Terpstra test, p-value = 0.084). According to Proposition 1, these results suggest a degree of diminishing sensitivity γ (relative thinking ρ)

close to one for AMT workers. To confirm these results, we conducted three additional robustness checks, see Subsection 6.1 and Subsection 6.2. They yield roughly the same outcomes.

Among student subjects, the share of searchers again 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 $S7.0$. Although this increase is statistically significant (Jonckheere-Terpstra test, p-value = 0.006), it is largely driven by a small share of subjects who search a lot of shops in high scale treatments. 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 according to Proposition 1 suggests a degree of diminishing sensitivity γ (relative thinking ρ) below one.

Very few subjects take breaks between searches. Among students subjects, 25 searchers (5.1 percent) take at least one break of two or more minutes between searches. Among AMT workers, only 14 searchers (2.7 percent) take at least one such break.

Search Time. The mean search duration is roughly 85 seconds for AMT workers and 60 seconds for student subjects. There are no significant differences between treatments (one-way ANOVA, p-value = 0.700 for AMT workers, and p-value = 0.626 for students subjects). For AMT workers, there are no significant differences in the mean total duration between treatments (one-way ANOVA, p-value = 0.788). 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 again driven by a few subjects who search extensively in high scale treatments.

For the AMT workers, we derive a direct measure of search costs. We use an AMT worker's opportunity costs of one hour of work on AMT and the time she needs on average to obtain a price quote. The direct search cost measure is defined by

$$\text{direct search costs} = \text{average hourly earnings} \times \frac{\text{mean search duration}}{3600}. \tag{8}$$

It captures the amount of money the searcher could earn by working in another job on AMT instead of searching one more shop. We find that the average direct search costs of the AMT workers in our sample are 0.16 USD (sd = 0.28). For our student subjects, the information about direct search costs is less precise. From the average earnings in experiments and subjects' mean search duration we may conjecture that these are around 0.25 Euro. However, this is most likely an upper bound on student subjects' average direct search costs since at the time when the experiments took place there were no other online experiments.

Table 2: Descriptive Statistics – Search Behavior and Search Time

	Price Scale	Share Searchers	Mean No. Searches if search	Median No. Searches if search	Gain Share if search
			Panel A: 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]	0.85	3.5 (6.8)	1	0.65
N		626	528	528	528
			Panel B: 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, 56.00]	0.83	11.5 (17.2)	6	0.93
N		581	490	490	490

	Price Scale	Mean Search Duration	Median Search Duration	Mean Total Duration	Median Total Duration
			Panel A: 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
N		516	528	503	528
			Panel B: Student Subjects		
$S1.0$	[4.00, 8.00]	62 (32)	55	464 (425)	359
$S3.0$	[12.00, 24.00]	65 (36)	53	520 (558)	382
$S5.0$	[20.00, 40.00]	62 (30)	55	658 (602)	562
$S7.0$	[28.00, 56.00]	60 (33)	54	758 (956)	455
N		487	490	469	490

Notes: Search Duration and Total 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.

Search Paradigm. We follow De los Santos et al. (2012) to examine whether search behavior in our experiment is more in line with sequential or non-sequential search; see Appendix A.3 for all details. We consider the following two key statistics. First, according to the sequential search model, subjects should purchase the good from the last sampled shop or search all shops. In contrast, according to the non-sequential search model, the probability of trading should be the same for all sampled shops. We find that 87.7 percent of AMT workers and 59.4 percent of student subjects purchase from the last sampled shop (or search all 100 shops); the probability of trading with the last sampled shop is significantly larger than the probability of trading with any other previously sampled shop.

Second, according to the sequential search model, the probability of continuing search should be positively correlated with the price of the last sampled shop. In contrast, according to non-sequential search, no such correlation should exist. We find a significant positive relationship between the probability of continuing search and the observed price. Thus, we conclude that the sequential search model is roughly consistent with sequential search and inconsistent with non-sequential search.

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 of the standard model, which we can directly infer from observed prices. In Subsection 5.2, we present the ordered probit framework with which we can jointly estimate search costs and the degree of diminishing sensitivity (or, after some adjustments, the degree of relative thinking). In Subsection 5.3, we show our estimation results. Finally, in Subsection 5.4, we examine the welfare consequences of context effects in our setting.

5.1 Lower and Upper Bounds of Search Costs in the Standard Model

To get a first 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 there are no context effects, as in the standard search model. Using the sequential search model from Section 2, we can infer search costs from reservation prices. In each treatment, 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 (5), we get that for $v(p, F) = p$, her search costs equal

$$c(r) = \frac{(r - a)^2}{2(b - a)}. \tag{9}$$

If we could observe a subject's reservation price r, we could immediately back out her search costs from the above function $c(r)$. Unfortunately, we do not observe r directly. However, we can infer r from subjects' search behavior in relation to the observed prices. Denote by $p_i^1, p_i^2, ..., p_i^{n_i}$ the set of subject i's 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 subject i searches $n_i \in \{2, ..., 99\}$ times, her search costs must be in the interval $c(p_i^1) \leq c_i \leq c(p_i^2)$. If subject i searches exactly once, her search costs must be in the interval $c(p_i^1) \leq c_i \leq c(b)$. Finally, if subject i searches all 100 shops, her search costs must be in the interval $-\infty < c_i \leq c(p_i^1)$.

Table 3: Lower and Upper Bounds on Search Costs in the Standard Model

	Price Scale	Mean Lower Bound Search Costs	Mean Upper Bound Search Costs
		Panel A: AMT Workers	
$S0.5$	[2.00, 4.00]	0.175 (0.023)	0.666 (0.036)
$S1.5$	[6.00, 12.00]	0.513 (0.062)	2.203 (0.094)
$S2.5$	[10.00, 20.00]	1.083 (0.117)	3.676 (0.168)
$S3.5$	[14.00, 28.00]	1.473 (0.161)	5.003 (0.222)
Observations		528	528
		Panel B: Student Subjects	
$S1.0$	[4.00, 8.00]	0.069 (0.013)	0.586 (0.060)
$S3.0$	[12.00, 24.00]	0.121 (0.019)	1.926 (0.211)
$S5.0$	[20.00, 40.00]	0.181 (0.036)	2.331 (0.308)
$S7.0$	[28.00, 56.00]	0.158 (0.041)	2.849 (0.396)
Observations		490	490

Notes: Standard errors are in parentheses.

We can now calculate for each treatment the mean lower and mean upper bound on search costs. Table 3 shows the results. Among AMT workers, the 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). For student subjects, we find similar results. Their mean lower bound increases from 0.07 Euro in treatment $S1.0$ to 0.16 Euro in treatment $S7.0$, and their mean upper bound on search costs increases from 0.59 Euro in treatment $S1.0$ to 2.85

Euro in treatment $S7.0$ (Jonckheere-Terpstra test, p-value < 0.001 in both cases).

These findings seem to suggest that search costs increase with the price scale, even though subjects were allocated randomly into scale treatments. There are no objective reasons for such an increasing relationship. Hence, one may instead interpret these findings as biased estimates in the standard search model and as an indication for context effects in both subject pools.

5.2 Ordered Probit Model

From the framework in Section 2, we derive an empricial model with which we can jointly estimate search costs and the extent of context effects in our experimental setting. In this subsection, we focus on the case of diminishing sensitivity. The case of relative thinking is very similar and we consider it when discussing our estimation results in Subsection 5.3.

To estimate search costs and the degree of diminishing sensitivity, we first derive search costs from reservation prices for any value of $\gamma \geq 0$. We generalize expression (9) for a uniform price distribution on $[a, b]$ and for reservation prices within this interval. From equation (5) and $v = v^{ds}$, we get that for $\gamma = 1$ her search costs would be equal to

$$c(r, \gamma = 1) = \frac{r - a + a(\ln a - \ln r)}{b - a}, \tag{10}$$

and for any $\gamma \in (0, 1) \cup (1, 2) \cup (2, \infty)$, her search costs would be given by

$$c(r, \gamma) = \frac{(1 - \gamma)r^{2-\gamma} - (2 - \gamma)ar^{1-\gamma} + a^{2-\gamma}}{(1 - \gamma)(2 - \gamma)(b - a)}. \tag{11}$$

Finally, for $\gamma = 2$, her search costs would equal

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

Since we do not observe reservation prices directly, we make a parametric assumption on the distribution over search costs across subjects. Specifically, we assume that the log of search costs is normally distributed and depends on a vector of subject characteristics. This is a common assumption in the search cost literature. We will relax it in Subsection 6.3 by considering a more flexible distribution. Denote by x_i the characteristics of subject $i \in \{1, ..., I\}$. The log of her search costs is given by

$$\ln c_i = x_i\beta + \sigma\varepsilon_i, \tag{13}$$

where ε_i follows a standard normal distribution Φ, β is a vector of parameters affecting the mean, and σ is the standard deviation of the distribution. With log-normally distributed search costs, we implicitly assume that all subjects exhibit positive search costs. Indeed, we have very few subjects who search all 100 shops (six student subjects and zero AMT workers).

The link between search costs and reservation wage established above and the parametric assumption in equation (13) give rise to an ordered probit model that we can estimate using maximum likelihood estimation. For each subject i with the number of searches $n_i \in \{2, ..., 99\}$, we observe the two smallest prices p_i^1, p_i^2 and, for a given degree of diminishing sensitivity γ, we obtain the likelihood contribution

$$\begin{aligned} P_i = \Pr(c(p_i^1,\gamma) \leq c_i < c(p_i^2,\gamma)) &= \Pr(c(p_i^1,\gamma) \leq \exp(x_i\beta + \sigma\varepsilon_i) < c(p_i^2,\gamma)) \\ &= \Phi\left(\frac{\ln c(p_i^2,\gamma) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma) - x_i\beta}{\sigma}\right). \end{aligned} \tag{14}$$

For the censored observations with $n_i = 1$, we have

$$\begin{aligned} P_i = \Pr(c(p_i^1,\gamma) \leq c < c(b,\gamma)) &= \Pr(c(p_i^1,\gamma) \leq \exp(x_i\beta + \sigma\varepsilon_i) < c(b,\gamma)) \\ &= \Phi\left(\frac{\ln c(b,\gamma) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma) - x_i\beta}{\sigma}\right). \end{aligned} \tag{15}$$

Similarly, for $n_i = 100$, we have

$$P_i = \Pr(c < c(p_i^1,\gamma)) = \Pr(\exp(x_i\beta + \sigma\varepsilon_i) < c(p_i^1,\gamma)) = \Phi\left(\frac{\ln c(p_i^1,\gamma) - x_i\beta}{\sigma}\right). \tag{16}$$

The log-likelihood function is given by

$$\ln L = \sum_{i=1}^{I} \ln P_i. \tag{17}$$

With this function, we can jointly estimate the distribution over search costs and the degree of diminishing sensitivity using maximum likelihood estimation.

5.3 Estimation Results

The Standard Model. In this subsection, we describe the results from our ordered probit regressions. We start with the standard case without context effects. Table 4 shows the results. For both subject pools, the parameter $\tilde{\beta}_0$ indicates the average search costs. When context effects are ignored, AMT workers incur on average search costs of 2.30 USD per search and student subjects 0.46 Euro per search. There is considerable unobserved heterogeneity in search costs. We estimate a standard deviation around the mean of 8.65 for AMT workers and of 2.00 for student subjects.

Table 4: Search Costs Estimates in Standard Model

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: AMT Workers			*Panel B: Student Subjects*		
$S0.5/S1.0$		0.424***	0.449***		0.247***	0.379***
		(0.069)	(0.106)		(0.050)	(0.124)
$S1.5/S3.0$		1.528***	1.564***		0.481***	0.731***
		(0.237)	(0.353)		(0.101)	(0.251)
$S2.5/S5.0$		2.860***	2.816***		0.551***	0.846***
		(0.444)	(0.638)		(0.113)	(0.293)
$S3.5/S7.0$		3.794***	3.702***		0.579***	0.872***
		(0.558)	(0.804)		(0.124)	(0.290)
$\tilde{\beta}_0$	2.296***			0.458***		
	(0.270)			(0.066)		
$\tilde{\sigma}$	8.648***	4.486***	4.034***	1.996***	1.816***	1.793***
	(1.779)	(0.739)	(0.648)	(0.502)	(0.447)	(0.439)
γ	0.000	0.000	0.000	0.000	0.000	0.000
Controls	No	No	Yes	No	No	Yes
Observations	528	528	528	490	490	490

Notes: Separate search costs per treatment, based on ordered probit (17) with γ fixed at value zero; $\tilde{\beta}_0$, the scale dummies, and $\tilde{\sigma}$ are transformed estimates reflecting average search costs and the standard deviation of search costs, respectively. More specifically, $\tilde{\beta}_0 = \exp(\beta_0 + \frac{\sigma^2}{2})$; $\tilde{\beta}_j = \exp(\beta_j + \frac{\sigma^2}{2})$ with $j \in \{1, ..., 4\}$ indicating the number of the scale dummy ordered by size; $\tilde{\sigma} = \sqrt{\exp(2\bar{x}\beta + \sigma^2)(\exp(\sigma^2) - 1)}$, where $\bar{x} = \frac{1}{I}\sum_{i=1}^{I} x_i$. 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 *** $p < 0.01$.

The estimated search costs differ substantially between treatments, see Columns 2 and 5 of Table 4. 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. Similar, for student subjects, the average search costs per search are only 0.25 Euro in treatment $S1.0$ and they reach 0.58 Euro in treatment $S7.0$, an increase of 134 percent. These differences are statistically significant in both cases (p-value < 0.001 and p-value < 0.006, respectively). Importantly, the estimated search costs are substantially larger than the direct search costs (these were 0.16 USD for AMT workers and 0.25 Euro for student subjects). This is particularly true for the AMT workers where the estimated search costs in the highest scale treatment are more than 20 times larger than the average direct search costs.

Observe that the search cost estimates fall within the average lower and upper bounds of Table 3. Columns 3 and 6 show 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 risk and CRT score. We obtain roughly the same results when we include these controls (they are not significant). Hence, under the standard random sequential search model, empirical search cost estimates are large and increasing in the price scale. This replicates the findings from empirical search cost literature that we highlighted in the introduction. Since the physical search costs are the same in all treatments, the estimation most likely captures a misspecification bias.

Table 5: Search Model with Diminishing Sensitivity (γ estimated)

	(1)	(2)	(3)	(4)
	Panel A: AMT workers		*Panel B: Student Subjects*	
$\tilde{\beta}_0$	0.171***	0.191***	0.138***	0.209**
	(0.040)	(0.054)	(0.050)	(0.092)
$\tilde{\sigma}$	0.370***	0.373***	0.542**	0.547**
	(0.104)	(0.103)	(0.229)	(0.229)
γ	0.975***	0.937***	0.415***	0.408***
	(0.089)	(0.089)	(0.120)	(0.119)
Controls	No	Yes	No	Yes
Observations	528	528	490	490

Notes: Single search cost parameter across treatments, based on ordered probit (17) with flexible γ; $\tilde{\beta}_0$ and $\tilde{\sigma}$ are transformed estimates reflecting average search costs and the standard deviation of search costs, respectively. More specifically, $\tilde{\beta}_0 = \exp(\beta_0 + \frac{\sigma^2}{2})$; $\tilde{\sigma} = \sqrt{\exp(2\bar{x}\beta + \sigma^2)(\exp(\sigma^2) - 1)}$, where $\bar{x} = \frac{1}{I}\sum_{i=1}^{I} x_i$. Standard errors are in parentheses. The controls are the same as in Table 4. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The Model with Diminishing Sensitivity. Columns 1 and 3 of Table 5 show the results from our ordered probit regressions with flexible γ for both subject groups. For AMT workers, we find 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 different from zero (p-value < 0.001) and very close to, and insignificantly different from one. For student subjects, the ordered probit regressions yield us a degree of diminishing sensitivity of $\gamma = 0.42$ and average search costs per search of 0.14 Euro. The diminishing sensitivity parameter is again significantly different from zero (p-value < 0.001), but significantly smaller than one. For both subject groups, estimated search costs are now roughly in line with direct search costs; for AMT workers the two numbers are almost exactly the same.

Table 6: Search Costs Estimates with/without Diminishing Sensitivity (γ fixed)

	(1)	(2)	(3)	(4)
	Panel A: AMT Workers		*Panel B: Student Subjects*	
$S0.5/S1.0$	0.139***	0.424***	0.124***	0.247***
	(0.020)	(0.069)	(0.024)	(0.050)
$S1.5/S3.0$	0.169***	1.528***	0.155***	0.481***
	(0.023)	(0.237)	(0.032)	(0.101)
$S2.5/S5.0$	0.190***	2.860***	0.144***	0.551***
	(0.026)	(0.444)	(0.029)	(0.113)
$S3.5/S7.0$	0.183***	3.794***	0.133***	0.579***
	(0.024)	(0.558)	(0.028)	(0.124)
$\tilde{\sigma}$	0.364***	4.486***	0.541***	1.826***
	(0.052)	(0.739)	(0.128)	(0.447)
γ	0.975	0.000	0.415	0.000
Controls	No	No	No	No
Observations	528	528	490	490

Notes: Separate search costs per treatment, based on ordered probit (17) with γ fixed at the estimated values from Table 5 and at zero (as in Table 4). The scale dummies and $\tilde{\sigma}$ are transformed estimates reflecting average search costs and the standard deviation of search costs, respectively. More specifically, $\tilde{\beta}_j = \exp(\beta_j + \frac{\sigma^2}{2})$ with $j \in \{1, ..., 4\}$ indicating the number of the scale dummy ordered by size; $\tilde{\sigma} = \sqrt{\exp(2\bar{x}\beta + \sigma^2)(\exp(\sigma^2) - 1)}$, where $\bar{x} = \frac{1}{I}\sum_{i=1}^{I} x_i$. Standard errors are in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

We compare the estimated search costs per treatment from the modified model with those from the standard model. Table 6 shows the results in Column 1 for AMT workers and in Column 3 for student subjects, at the estimated value of γ from Table 5 (from Columns 1 and 3). In Columns 2 and 4, we again show the regression results under the assumption that there are no context effects (i.e., Columns 2 and 5 from Table 4) to facilitate the comparison. For AMT workers, the average search costs per search vary between 0.14 USD and 0.19 USD. As expected, the differences are not significant (p-value > 0.100). For student subjects, the average search costs per search vary between 0.12 Euro and 0.16 Euro. Again, these differences are never significant (p-value > 0.367). The estimated search costs are substantially smaller when we allow for diminishing sensitivity. Thus, in the highest scale treatments, a large part of the standard search cost estimates are due to scale: 95 percent in $S3.5$ for AMT workers and 77 percent in $S7.0$ for student subjects.

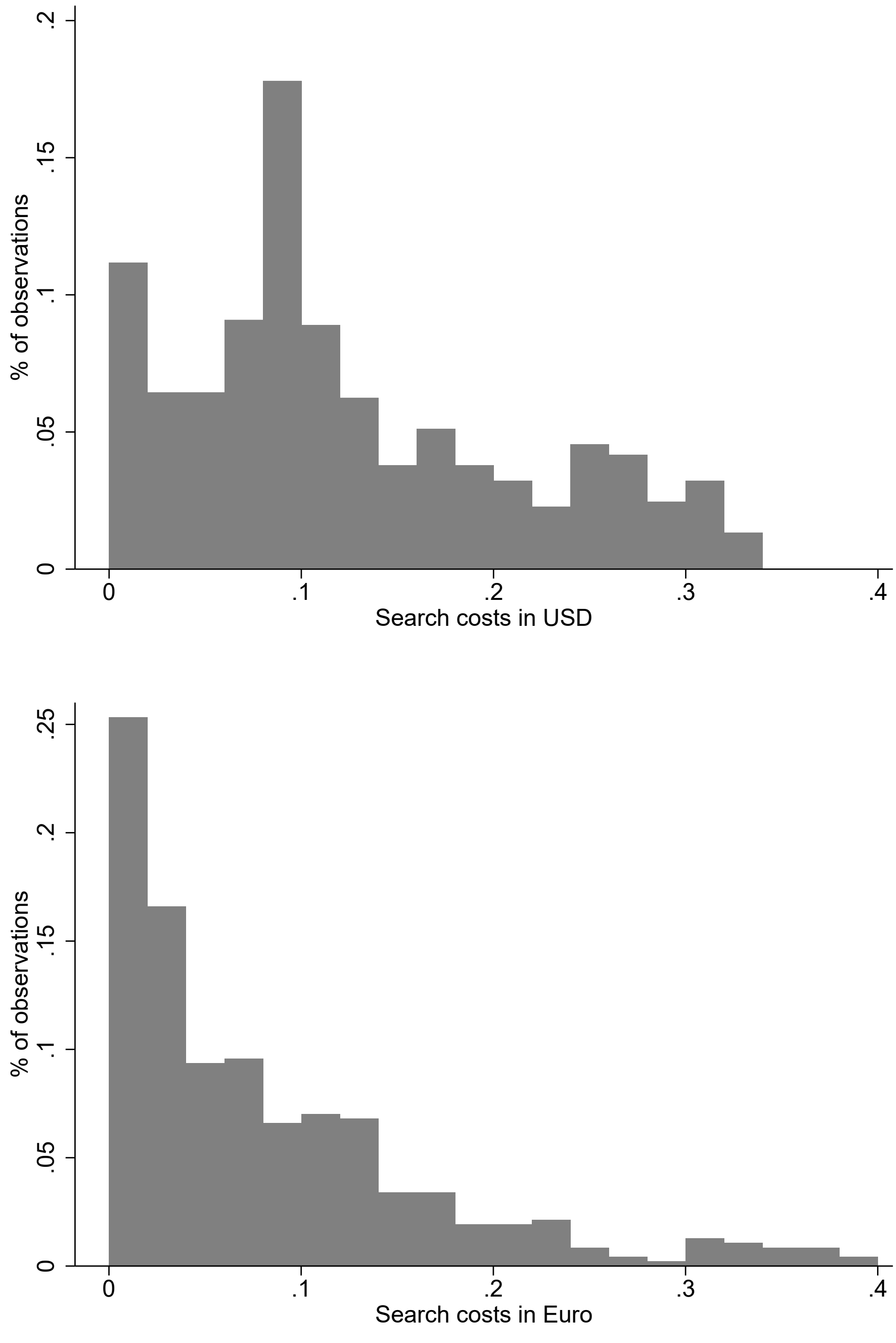


Figure 1: Distribution of expected individual search costs per search (bin width = 0.02 USD/Euro) for AMT workers (upper graph) and student subjects (lower graph), for flexible degrees of diminishing sensitivity.

The estimated search costs are also quite similar for students and AMT workers.[13] In contrast, when we assume that there are no context effects, the average search costs of AMT workers are 4.4 times larger than those of student subjects.

The Role of Unobserved Heterogeneity. Next, we examine whether subject characteristics can partly explain unobserved heterogeneity in search costs. In Columns 2 and 4 of Table 5, we consider our results from the ordered probit regression when 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 risk (coefficient = 0.10, se = 0.04) and above-median CRT score (coefficient = -0.05, se = 0.03) are statistically significant. These results suggest that AMT workers who are more willing to take risks have higher search costs, and that those 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. We also consider a specification where we interact γ with the control variables. None of the controls plays a significant role. Hence, there is no heterogeneity in γ along our control variables.

The result on the relationship between search costs and willingness to take risk is relevant, for the following reason. A common intuition is that risk-averse individuals search less in order to avoid disappointing outcomes. This intuition is not supported by our data. Instead, individuals who are less willing to take risks invest more into search. One explanation could be that, by searching more, one reduces the probability of paying a high price, and, as the number of searches becomes large, this probability converges to zero.

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 $[c(p^1, \gamma), c(p^2, \gamma)]$, see Appendix A.4 for formal details. Figure 1 shows this distribution separately for AMT workers and student subjects. There is substantial heterogeneity in both subject pools. For AMT workers, the distribution exhibits two peaks, one around very small search costs and one around 0.08 USD. For student subjects, the distribution has a single peak around very small search costs.

The Model with Relative Thinking. We show that using the relative thinking parametrization instead of the diminishing sensitivity model yields quantitatively very similar results. With

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

uniformly distributed prices, we obtain from equation (5) and $v = v^{rt}$ that the decision-maker's search costs for a given reservation price r are equal to

$$c(r, \rho) = \frac{1}{\Delta_F^{\rho}} \frac{(r-a)^2}{2(b-a)}. \tag{18}$$

Using our ordered probit regression framework from Subsection 5.2 we can then jointly estimate search costs and the degree of relative thinking ρ. We only replace the search cost function $c(r, \gamma)$ by the new function $c(r, \rho)$. Columns 1 and 3 of Table 7 show the results from our ordered probit regressions with flexible ρ.

Table 7: Search Model with Relative Thinking (ρ estimated)

	(1)	(2)	(3)	(4)
	Panel A: AMT workers		*Panel B: Student Subjects*	
$\tilde{\beta}_0$	0.196***	0.214***	0.138***	0.210***
	(0.041)	(0.058)	(0.046)	(0.087)
$\tilde{\sigma}$	0.512***	0.501***	0.571***	0.573**
	(0.127)	(0.122)	(0.220)	(0.219)
ρ	1.141***	1.098***	0.457***	0.450***
	(0.097)	(0.095)	(0.119)	(0.118)
Controls	No	Yes	No	Yes
Observations	528	528	490	490

Notes: Single search cost parameter across treatments, based on ordered probit (17) with flexible ρ; $\tilde{\beta}_0$ and $\tilde{\sigma}$ are transformed estimates reflecting average search costs and the standard deviation of search costs, respectively; $\tilde{\beta}_0 = \exp(\beta_0 + \frac{\sigma^2}{2})$; $\tilde{\sigma} = \sqrt{\exp(2\bar{x}\beta + \sigma^2)(\exp(\sigma^2) - 1)}$, where $\bar{x} = \frac{1}{I}\sum_{i=1}^{I} x_i$. Standard errors are in parentheses. The controls are the same as in Table 4. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

For AMT workers, we find a degree of relative thinking of $\rho = 1.14$, which does not differ significantly from 1, and average search costs per search of 0.20 USD. For student subjects, we find a degree of relative thinking of $\rho = 0.46$ and average search costs per search of 0.14 Euro. The degree of relative thinking is significantly different from zero (p-value < 0.001). It is relatively close to the estimate from Somerville (2022), which equals $\rho = 0.34$. Importantly, the search cost estimates for both subject pools are fairly close to those that we obtained from the diminishing sensitivity model.

In Columns 2 and 4 of Table 7, we consider the results from the same regression where we additionally take into account our standard control variables. For student subjects, no control variable is significant. For AMT workers, the dummy variables for above-median willingness to take risk (coefficient = 0.123, se = 0.047) and above-median CRT score (coefficient = -0.058, se = 0.033) are statistically significant (and there is a slight drop in σ, measuring unobserved heterogeneity in search costs). In a regression where ρ depends on our standard controls, we do not see any variable with a significant coefficient. Again, these results are quite in line with those from the diminishing sensitivity model.

We compare the estimated average search costs between treatments for given (estimated) values of ρ. Table A5 in the Appendix shows the results in Column 1 for AMT workers and in Column 3 for student subjects. In Columns 2 and 4, we again display the regression results from the standard model ($\rho = 0$). For AMT workers, the average search costs per search vary between 0.19 USD and 0.21 USD. These differences are never significant (p-values > 0.602). For student subjects, the average search costs per search vary between 0.13 Euro and 0.15 Euro. Again, these differences are never significant (p-values > 0.434).

5.4 Welfare

Using our utility framework, we can assess the welfare consequences of context effects in our experiment and at large price scales. Following the literature, we define the welfare loss as the difference between the experienced utility in the absence of context effects and the experienced utility when decision-making is subject to context effects. We first derive the absolute welfare loss of a decision-maker who exhibits diminishing sensitivity of degree γ; the case of relative thinking proceeds similarly. For given search costs c, let r be the reservation price in the classical search model defined by equation (2), and r_γ the reservation price under diminishing sensitivity defined by equation (5) when $v = v^{ds}$. The decision-maker's (expected) experienced utility from search is given by

$$u - \mathbb{E}[p \mid p \leq r_\gamma] - \frac{c}{F(r_\gamma)}. \tag{19}$$

The absolute welfare loss from diminishing sensitivity then equals the difference in the payoffs from equations (3) and (19):

$$\text{absolute welfare loss} = \Big(\mathbb{E}[p \mid p \leq r_\gamma] - \mathbb{E}[p \mid p \leq r]\Big) + \left(\frac{1}{F(r_\gamma)} - \frac{1}{F(r)}\right)c. \tag{20}$$

The absolute welfare loss consists of a change in the expected price and a change in expected search costs. If $r_\gamma > r$, the decision-maker searches too little relative to the rational benchmark. In this case, the expected price increases while expected total search costs decrease – the net effect is negative. For the uniform distribution on the interval $[a, b]$, the expression for a decision-maker's absolute welfare loss from equation (20) becomes

$$\frac{1}{2}(r_\gamma - r) - \frac{(r_\gamma - r)(b-a)}{(r_\gamma - a)(r-a)}c. \tag{21}$$

Next, we derive the decision-maker's relative welfare loss in our experimental setting. For this, we normalize her utility by taking out the product payoff u. If the decision-maker does not search at all, then, in our setting, her payoff is $u - b$. We substract this from the payoff defined in (3) and obtain the absolute utility gains from search. It is equal to

$$b - \mathbb{E}[p \mid p \leq r] - \frac{c}{F(r)}. \tag{22}$$

If F is the uniform distribution on the interval $[a, b]$, the corresponding reservation price equals $r = a + \sqrt{2(b-a)c}$. The decision-maker's absolute utility gains from search then is given by

$$(b-a) - \sqrt{2(b-a)c}. \tag{23}$$

The ratio between the absolute welfare loss in equation (21) and the absolute utility gains from search in equation (23) constitute her relative welfare loss.

We compile the relative welfare loss in our setting for varying search costs, price scales, as well as degrees of diminishing sensitivity and relative thinking. For search costs, we choose $c \in \{0.05, 0.15, 0.30\}$ which corresponds to relatively small, intermediate, and relatively large values for both AMT workers and student subjects in our setting; see the distribution over expected search costs in Figure 1. For degrees of diminishing sensitivity and relative thinking, we select the values $\gamma \in \{0.40, 0.70, 1.00\}$ and $\rho \in \{0.50, 0.75, 1.00\}$, respectively. Hence, we have, roughly, the AMT workers' and student subjects' levels of context effects as well as an intermediate level. For price scales, we take the original scales from our experiment as well as a few high price scales.

Table 8 shows the results. For small levels of context effects, the relative welfare loss is fairly modest, even for subjects with substantial search costs, or for very high price scales. Typically, it is less than 6 percent of the absolute welfare. This also holds for higher prices. In contrast, for large levels of context effects, we find substantial welfare losses among all search cost levels. At high price scales, subjects with small search costs lose more than 10 percent of the absolute gains from search, and subjects with high search costs lose almost 50 percent (here the values are slightly lower under the relative thinking parametrization). Observe that the relative welfare loss is often not increasing monotonically in the price scale, in particular at lower levels of context effects. At a sufficiently large scale, the relative welfare loss then drops. In summary, the welfare loss due to diminishing sensitivity can be quite substantial.

Table 8: Relative Welfare Loss – Comparative Statics

	$\gamma = 0.40$			$\gamma = 0.70$			$\gamma = 1.00$		
c	0.05	0.15	0.30	0.05	0.15	0.30	0.05	0.15	0.30
$z = 0.5$	<0.01	0.01	0.03	0.01	0.04	0.09	0.03	0.09	0.22
$z = 1.0$	0.01	0.02	0.04	0.03	0.07	0.13	0.06	0.15	0.30
$z = 3.5$	0.01	0.03	0.04	0.05	0.09	0.15	0.11	0.23	0.39
$z = 7.0$	0.02	0.03	0.04	0.05	0.10	0.16	0.13	0.26	0.42
$z = 10$	0.02	0.03	0.04	0.05	0.10	0.16	0.14	0.27	0.43
$z = 100$	0.01	0.02	0.03	0.05	0.09	0.14	0.16	0.31	0.47
$z = 1000$	0.01	0.02	0.02	0.04	0.07	0.11	0.17	0.32	0.49
	$\rho = 0.50$			$\rho = 0.75$			$\rho = 1.00$		
c	0.05	0.15	0.30	0.05	0.15	0.30	0.05	0.15	0.30
$z = 0.5$	<0.01	0.01	0.02	0.01	0.02	0.04	0.02	0.04	0.07
$z = 1.0$	0.01	0.02	0.04	0.03	0.05	0.09	0.05	0.09	0.16
$z = 3.5$	0.02	0.04	0.06	0.05	0.09	0.14	0.09	0.17	0.26
$z = 7.0$	0.02	0.04	0.06	0.06	0.10	0.15	0.11	0.20	0.30
$z = 10$	0.02	0.04	0.06	0.06	0.11	0.16	0.12	0.21	0.31
$z = 100$	0.02	0.04	0.05	0.06	0.11	0.15	0.14	0.25	0.36
$z = 1000$	0.02	0.03	0.04	0.05	0.09	0.13	0.15	0.27	0.38

6 Robustness and Extensions

We discuss a number of factors that may influence our estimation results or may provide alternative explanations for our findings. In Subsection 6.1, we discuss alternative reasons for why AMT workers spend relatively little effort on search, and we examine the results from two additional robustness checks with new samples of AMT workers. In Subsection 6.2, we report the results of a further robustness check in which AMT workers search for two products of varying price scales. In Subsection 6.3, we relax the assumption that search costs are log-normally distributed. Finally, in Subsection 6.4, we discuss why increasing search costs are unlikely to explain our results.

6.1 Search on Amazon Mechanical Turk

The AMT workers in our sample spend relatively little effort on search, despite substantial incentives. Such behavior is not uncommon in many online search settings. For example, Ursu et al. (2022) also report a median number of one visited website and a median duration of search of one minute for the product category of apparel. Nevertheless, one may suspect that a lack of understanding or attention partially drives the results in our setting. We conduct a number of robustness checks to show that these factors are unlikely to explain our findings. First, we restrict the sample to AMT workers who indicate to have a university degree (Bachelor's or Master's degree). These are 74.1 percent of all AMT workers in our sample. Second, we restrict the sample to AMT workers with a CRT score of 2 or 3; these are 56.7 percent of the sample. Finally, we consider the median split with respect to time spent on Part 1 of the experiment and restrict the sample to subjects who spend more time than the median (around 6.7 minutes). If a lack of understanding or attention are relevant factors, then in these subsamples we should arguably observe more search and a smaller level of context effects. The estimation results are as follows:

AMT sample used for estimation	$S0.5$ Mean No. Searches	$S3.5$ Mean No. Searches	Estimated γ / ρ	Estimated Search Costs
all subjects	2.9 (4.1)	3.5 (6.8)	0.98 / 1.14	0.17 / 0.20
university degree only	2.7 (4.5)	2.9 (4.2)	1.02 / 1.15	0.15 / 0.18
high CRT score	3.3 (4.9)	4.1 (7.7)	1.03 / 1.16	0.12 / 0.15
Part 1 above median time	2.9 (5.0)	4.2 (9.1)	0.91 / 1.12	0.24 / 0.24

In all subsamples, the amount of search as well as the estimated parameter values for search costs and the degree of diminishing sensitivity/relative thinking slightly vary around those of the full sample. Only for the AMT workers who spent above-median time on Part 1 we observe a smaller level of context effects. Overall, the estimated parameter values are close to our original results. Hence, there is little indication that misunderstandings or a lack of attention have a sizable impact on our results for the AMT workers.

To further evaluate search on AMT, we conduct two robustness checks with a new sample of 610 AMT workers (around four months after the baseline study). In Robustness Check 1, we highlight in the invitation to our HIT that the study consists of two parts, and that subjects can work as long as they want in the second part to earn additional money. Our goal here was to adjust workers' expectations about the time frame of our HIT. In Robustness Check 2, we ask a comprehension question at the end of the instructions to the second part that highlights the gains from search. Specifically, we ask subjects about their money earnings if they purchase the product at a particular price. This price was set so that 60 percent of the maximal possible price savings would be realized. Thus, the money earnings increase in the price scale. We conducted both robustness checks for the treatments $S0.5$ and $S3.5$. All details on the robustness checks can be found in Appendix A.5.

Table A9 and Table A10 in the appendix contain the demographic information as well as the most important results on average search behavior, search time, as well as direct and estimated search costs. In both robustness checks, search behavior is fairly similar to that in the baseline study with AMT workers. As long as we do not take context effects into account, estimated search costs increase by a factor of five from $S0.5$ to $S3.5$. With the updated models, we obtain the following results.

	$S0.5$ Mean No. Searches	$S3.5$ Mean No. Searches	Estimated γ / ρ	Estimated Search Costs	Direct Search Costs
Robustness Check 1	1.9 (1.9)	3.3 (5.2)	0.79 / 0.84	0.25 / 0.34	0.33
Robustness Check 2	2.3 (2.7)	3.1 (4.6)	0.76 / 0.85	0.27 / 0.33	0.17

Thus, the estimated degrees of diminishing sensitivity/relative thinking are slightly smaller and the estimated search costs slightly larger than in the baseline study (the standard errors remain comparable). However, direct search costs are also somewhat larger in the new samples. We conclude that our results are robust to variations in the framing of the search context. Nevertheless, it may be the case that more information about possible gains from search slightly reduces the level of context effects. That being said, it needs to be mentioned that in a typical online search environment the benefits from search are not made salient to consumers and searching at different shops or platforms is not particularly encouraged. Therefore, the level of context effects in the robustness checks $R1$ and $R2$ may be a conservative estimate.

6.2 Multi-Item Search

Do context effects vanish if subjects can search multiple items? One may argue that if individuals have to search for several products with varying price levels, they understand that it is optimal to exert more search effort when prices are high and the price dispersion is large. To examine whether this is the case, we conduct a version of our experiment (Robustness Check 3) where subjects can buy two products, Product A and Product B. The price scales of the two products are again $S0.5$ and $S3.5$; the assignment of price scale to product is random. Subjects can search up to 100 product A online shops and up to 100 product B online shops, in any order. All previously searched shops can be accessed from an overview screen. Appendix

A.6 contains the adjusted instructions. For this experiment, we recruit a new sample of 191 ATM workers.

Table A11 and Table A12 in the appendix contain the demographic information as well as the most important results on average search behavior, search time, as well as direct and estimated search costs. Our main results are as follows.

	$S0.5$ Mean No. Searches	$S3.5$ Mean No. Searches	Estimated γ / ρ	Estimated Search Costs	Direct Search Costs
Robustness Check 3	1.3 (1.4)	1.7 (3.0)	0.93 / 0.95	0.22 / 0.32	0.18

We obtain similar results if we include fixed effects for subjects who purchase both products in our regressions, i.e., $\gamma = 0.97$ ($\rho = 0.96$) and search costs of 0.23 USD (0.36 USD) per search. Overall, search behavior is very similar in the two price scales. Subjects search slightly more in scale $S3.5$ than in scale $S0.5$ (one-sided t-test, p-value = 0.077), but the estimated search costs from the standard model are again very different under the two scales when we naively treat search in the two scales as separate datasets: 0.61 USD under scale $S0.5$ and 3.87 USD under scale $S3.5$. Hence, the extent of context effects remains strong even when individuals can search simultaneously in varying scales. We estimate $\gamma = 0.93$ and $\rho = 0.95$, each precisely estimated with a standard error of 0.06.

6.3 Search Cost Distribution

For our ordered-probit model, we assumed that search costs are log-normally distributed. An alternative assumption is that search costs are normally distributed, which allows for the possibility of negative search costs. More generally, we can relax the distributional assumption by applying a Box-Cox transformation (Box and Cox 1964). It transforms a non-normal dependent variable c into a normally distributed variable. Its functional form is

$$g(c) = \frac{c^{\lambda} - 1}{\lambda} \text{ if } \lambda \neq 0 \text{ and } g(c) = \ln c \text{ if } \lambda = 0. \tag{24}$$

In a Box-Cox transformation, the value λ is chosen so that the transformed distribution most closely resembles a normal distribution. We conduct a Box-Cox transformation on search costs within our ordered probit regression framework with flexible context effect parameters and λ using maximum likelihood estimation. Moreover, we estimate the context effect parameters for fixed values $\lambda = 0$ (log-normally distributed search costs) and $\lambda = 1$ (normally distributed search costs).

Table A13 and Table A14 in the appendix show the results for the model with diminishing sensitivity and relative thinking, respectively. For AMT workers, the estimated degree of diminishing sensitivity γ (relative thinking ρ) lies between 0.98 and 1.07 (1.06 and 1.14); the estimated Box-Cox parameter λ is 0.50 (0.43) and the corresponding γ is 1.05 (1.08). For student subjects, the estimated degree of diminishing sensitivity γ (relative thinking ρ) varies between 0.42 and 0.69 (0.46 and 0.6). The estimated Box-Cox parameter λ equals 0.16 (0.14). Hence, for student subjects the distribution of search costs is close to the log-normal distribution; the corresponding γ (ρ) equals 0.51 (0.5). We conclude that our main results regarding context effects continue to hold under a distributional assumption on search costs that is more flexible than the assumption of log-normality.

6.4 Increasing Search Costs

The classic sequential search model assumes that search costs per search are constant in the number of searches. Many empirical search models stick to this assumption. However, in general, it may also be possible that search costs increase in the number of searches, depending on the search environment. For AMT workers in our study, the number of searches increases only slightly, from 2.9 in treatment $S0.5$ to 3.5 in treatment $S3.5$ (and this increase is not statistically significant). Overall, they spend on average less than 5 minutes on search, but work for many hours on AMT. Hence, it seems unlikely that increasing search costs can rationalize their behavior. However, increasing search costs could, in principle, explain the student subjects' search behavior and the rise in their search cost estimates. Nevertheless, there are several reasons why this is quite implausible.

First, increasing search costs are unlikely to explain our results because subjects have several days to complete the task and they can have breaks at their discretion after each search. Hence, they are not forced to start or to continue search when it is inconvenient for them. Note that this is a major difference to real-effort tasks that take place in a limited period of time and where performance cannot easily be increased.[14] However, as discussed in Subjection 4.2, few student subjects (around 5 percent) have a break between searches.[15] Therefore, we believe that increasing search costs cannot explain the scale-dependency of the students' search cost estimates.

Second, search in our setting is akin to a simple data entry job that does not require cogni-

[14]For example, in DellaVigna and Pope (2018) subjects have to press alternating keys as quickly as possible for ten minutes. In this setting, there are tight physical limits on performance so that effort costs must be convex.

[15]In contrast, Ursu et al. (2022) find for search in the product category of apparel that 43 percent of consumers take at least one break while searching. They suggest that these breaks occur due to search fatigue. However, the products in their settings have many dimension consumers may take into account when making comparisons (design, color, materials, asf.), while in our experiment products are homogeneous and only vary in prices.

tive effort and for which it is common to hire students as research assistants; their wage would be around 13.50 Euro per hour in Innsbruck and the hourly wage promised to experimental subjects is 15.00 Euro per hour. A back-of-the-envelope calculation shows that if increasing search costs (instead of context effects) would explain our findings, this would imply unreasonably high hourly reservation wages for our student subjects. From Table 2 and from Table 4 we get that, in treatment $S1.0$, subjects spend on average 4.90 minutes on search and the estimated search costs implied by the last search equal 0.25 Euro. In treatment $S7.0$, subjects spend on average 12.63 minutes on search and the estimated search costs implied by the last search equal 0.58 Euro. Each search takes around 60 seconds so that the corresponding hourly reservation wage is on average 34.74 Euro in treatment $S7.0$. If search costs would further increase in a linear manner, then after one hour in this "data-entry job" the search costs per search would be 2.60 Euro[16], which implies an average hourly reservation wage of 156 Euro. This number would be even larger if we assume that search costs rise in a convex manner. Clearly, these numbers do not make much sense.

Finally, we can show that an empirical search model that captures increasing search costs, but abstracts from context effects, does not produce scale-independent search cost estimates. To this end, we incorporate the search cost function per search $c(n) = c_0 \times n^{\delta}$ with $c_0 > 0$, $\delta \geq 0$, and the number of searches $n > 0$ into our empirical model. Bushong and Gagnon-Bartsch (2022) use this functional form to estimate the curvature of effort costs in a real-effort experiment that elicits subjects' labor supply decisions. They estimate a δ of around 1.21. We use this functional form with fixed values of δ and abstract from context effects ($\gamma = 0$ and $\rho = 0$). We find that neither increasing and convex search costs ($\delta > 1$) nor increasing and concave search costs ($0 < \delta \leq 1$) can equalize the mean of estimated search costs c_0 in our four scale treatments. For student subjects, the ratio between the lowest and the highest mean search costs per scale is 1.8 or higher, whereas, for AMT workers, this ratio is around 9.[17] In contrast, in the previous section, allowing for context effects and assuming constant search costs, we obtain a ratio of 1.25 for students subjects and 1.37 for AMT workers.

7 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

[16]For this calculation we assume a linear time trend in search costs and use that the estimated search costs (for $\gamma = 0$) are, on average, 0.25 Euro after 4.90 minutes and 0.58 Euro after 12.63 minutes. We then obtain search costs per search of $0.58 + \frac{0.58-0.25}{12.63-4.90} \times (60 - 12.63) = 2.60$ Euro after 60 minutes.

[17]Further details are available from the authors upon request.

for digital markets are typically large and increasing in price scale of the product category. Therefore, search cost estimates are often difficult to reconcile with the time searchers need to identify different options. Why should the costs of finding a price quote online be several dollars when the required effort only takes a few seconds, especially when at the same time the searcher is willing to supply labor at a modest wage?

To study which mechanisms generate search cost estimates that are large and increasing in the price scale, we conducted an online search experiment with two crucial features: we precisely measure the time subjects need to identify a price quote, and we vary the price scale without changing the effort required to obtain a price quote. Hence, we can test whether estimated search costs reflect subjects' true opportunity costs of time and whether they mechanically increase in the price scale. At the same time, the experimental setting allows us to abstract from product complexity, seller reputation, and subjects' beliefs about the price distribution at each shop. Even in this controlled environment we find that the search cost estimates from a standard model greatly exceed the directly elicited search costs – in one case by a factor of more than 20 – and that they increase considerably in the price scale.

To explain large search cost estimates that increase in the price scale, we proposed that individuals exhibit context effects: They tend to become less sensitive to fixed price variations when the price scale of the product or range of potential outcomes increases. Therefore, they may undervalue the gains from search, in particular, when prices are high and the price dispersion is substantial. We modified the random sequential search model so that it allows for context effects. Specifically, we adopted two parametrizations that capture diminishing sensitivity and relative thinking, respectively. Taking context effects into account roughly equalizes the search cost estimates in different scale treatments. Most importantly, it also equalizes estimated and directly elicited search costs. We showed this for two very different subject pools, online workers on Amazon Mechanical Turk and student subjects from a convenience pool.

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 accurately reflect the effort required to identify options or searchers' opportunity costs of time, especially when they are large relative to the time needed to find an alternative. Our search cost estimates are considerably lower after accounting for context effects. Therefore, in many applications, the true time and hassle costs of search are most likely to be lower than suggested by standard search cost estimates. In the rest of this section, we briefly outline what our results imply for empirical work on search costs, and how future research can further examine the psychological mechanisms that lead to context effects in the search domain.

Implications for Empirical Work. Future empirical research on search costs can address the issue of scale-dependent search costs in a number of ways. First, one can adopt a more flexible specification than a linear price in the indirect utility function of the empirical search model. For example, if there are reasons to believe that only relative price savings matter for consumers, one may adopt a logarithmic price specification. This approach is not completely uncommon in the empirical industrial organization literature. Several papers have used a logarithmic price term to consider more flexible demand specifications, in particular, to relax the unit demand assumption (e.g., Björnerstedt and Verboven 2016). Our results provide a behavioral justification for this approach.

Second, in many online settings, it is probably easy to obtain direct search cost measures as we did for our two subject pools. Click data already contain the information necessary to get an estimate on the time consumers need to find product information and price quotes. Combining it with data on searchers' labor wages creates a benchmark to which one can compare search cost estimates. If the values of direct and estimated search costs differ substantially – even after taking context effects into account – this may indicate that searchers face further obstacles such as biased beliefs, complexity, or trust issues.

Third, it may be possible to obtain estimates for the level of context effects from observational data. Unlike in our experiment, it seems very difficult to get clean price scale variations for a given product in a real market setting to reliably identify the level of context effects. However, an alternative to price scale variations may be to study search for multiple items with differing price scales (as we did in one robustness check). Individual data on search for multiple items may even allow researchers to test whether there exist significant differences in the degree of diminishing sensitivity or relative thinking within the population.

Disentangling Behavioral Mechanisms. Our approach leaves open several other questions that researchers can address in future experimental and empirical work. We showed that both models of diminishing sensitivity and relative thinking can be used to obtain scale-independent search cost estimates. Thus, we were agnostic regarding the precise behavioral mechanism behind our findings. One can disentangle the two behavioral mechanisms in the domain of search, e.g., by varying the price scale while keeping the range of outcomes constant (and vice versa). This may also allow to estimate a search cost model that combines diminishing sensitivity and relative thinking in one utility framework. Finally, we largely ignored the price-setting behavior of firms, which we took as given. It may be interesting to study whether firms fully anticipate the scale-dependency of consumers' search costs as well as whether and how they adjust their marketing and price strategies to it.

References

AZAR, OFER (2007): "Relative thinking theory," *The Journal of Socio-Economics*, 36(1), 1–14.

AZAR, OFER (2011): "Do people think about absolute or relative price differences when choosing between substitute goods?," *Journal of Economic Psychology*, 32, 450–457.

BAYE, MICHAEL, JOHN MORGAN, AND PATRICK SCHOLTEN (2004): "Price dispersion in the small and in the large: Evidence from an internet price comparison site," *Journal of Industrial Economics*, 52(4), 463–496.

BERNHEIM, DOUGLAS, AND DMITRY TAUBINSKY (2018): "Behavioral public economics," *Handbook of Behavioral Economics: Applications and Foundations*, Volume 1, 381–516.

BJÖRNERSTEDT, JONAS, AND FRANK VERBOVEN (2016): "Does merger simulation work? Evidence from the Swedish analgesics market," *American Economic Journal: Applied Economics*, 8(3), 125–164.

BOCK, OLAF, INGMAR BAETGE, AND ANDREAS NICKLISCH (2012): "Hamburg registration and organization online tool," *European Economic Review*, 71, 117–120.

BORDALO, PEDRO, NICOLA GENNAIOLI, AND ANDREI SHLEIFER (2012): "Salience theory of choice under risk," *Quarterly Journal of Economics*, 127(3), 1243–1285.

BORDALO, PEDRO, NICOLA GENNAIOLI, AND ANDREI SHLEIFER (2013): "Salience and consumer choice," *Journal of Political Economy*, 121(5), 803–843.

BOX, GEORGE, AND DAVID COX (1964): "An analysis of transformations," *Journal of the Royal Statistical Society: Series B (Methodological)*, 26(2), 211–243.

BROWN, META, CHRISTOPHE FLINN, AND ANDREW SCHOTTER (2011): "Real-Time search in the laboratory and the market," *American Economic Review*, 101(2), 948–974.

BRYNJOLFSSON, ERIK, AND MICHAEL SMITH (2000): "Frictionless commerce? A comparison of Internet and conventional retailers," *Management Science*, 46(4), 563–585.

BURDETT, KENNETH, AND KENNETH JUDD (1983): "Equilibrium price dispersion," *Econometrica*, 51(4), 955–969.

BUSHONG, BENJAMIN, MATTHEW RABIN, AND JOSHUA SCHWARTZSTEIN (2021): "A model of relative thinking," *Review of Economics Studies*, 88(1), 162–191.

BUSHONG, BENJAMIN, AND TRISTAN GAGNON-BARTSCH (2022): "Reference dependence and attribution bias: Evidence from real-effort experiments," *American Economic Journal: Microeconomics*, forthcoming.

CASNER, BEN (2021): "Learning while shopping: An experimental investigation into the effect of learning on consumer search," *Experimental Economics*, 24, 232–260.

CASON, TIMOTHY, AND DANIEL FRIEDMAN (2003): "Buyer search and price dispersion: A laboratory study," *Journal of Economic Theory*, 112(2), 232–260.

CASON, TIMOTHY, AND SHAKUN MAGO (2010): "Costly buyer search in laboratory markets with seller advertising," *Journal of Industrial Economics*, 58(2), 424–449.

CAVALLO, ALBERTO (2017): "Are online and offline prices similar? Evidence from large multichannel retailers," *American Economic Review*, 107(1), 283–303.

DAVIS, DOUGLAS, AND CHARLES HOLT (1996): "Consumer search costs market performance," *Economic Inquiry*, 34(1), 133–151.

DELLAVIGNA, STEFANO, AND DEVIN POPE (2018): "What motivates effort? Evidence and expert forecast," *Review of Economic Studies*, 85(2), 1029–1069.

DE LOS SANTOS, BABUR (2018): "Consumer search on the Internet," *International Journal of Industrial Organization*, 58, 66–105.

DE LOS SANTOS, BABUR, ALI HORTAÇSU, AND MATTHIJS WILDENBEEST (2012): "Testing models of consumer search using data on web browsing and purchasing behavior," *American Economic Review*, 102(6), 2955–2980.

DE LOS SANTOS, BABUR, ALI HORTAÇSU, AND MATTHIJS WILDENBEEST (2017): "Search with learning for differentiated products: Evidence from e-commerce," *Journal of Business and Economic Statistics*, 35(4), 626–641.

DERTWINKEL-KALT, MARKUS, KATRIN KÖHLER, MIRJAM LANGE, AND TOBIAS WENZEL (2017): "Demand shifts due to salience effects: Experimental evidence," *Journal of the European Economic Association*, 15(3), 626–653.

DOHMEN, THOMAS, ARMIN FALK, DAVID HUFFMAN, UWE SUNDE, JÜRGEN SCHUPP, AND GERT G. WAGNER (2011): "Individual risk attitudes: Measurement, determinants, and behavioral consequences," *Journal of the European Economic Association*, 9(3), 522–550.

EINAV, LIRAN, THERESA KUCHLER, JONATHAN LEVIN, AND NEEL SUNDARESAN (2015): "Assessing sale strategies in online markets using matched listings," *American Economic Journal: Microeconomics*, 7(2), 215–247.

GABAIX, XAVIER (2014): "A sparsity-based model of bounded rationality," *Quarterly Journal of Economics*, 129(4), 1661–1710.

GHOSE, ANINDYA, PANAGIOTIS IPEIROTIS, AND BEIBEI LI (2017): "Modeling consumer footprints on search engines: An interplay with social media," *Management Science*, 65(3), 1363–1385.

GIULIETTI, MONICA, MICHAEL WATERSON, AND MATTHIJS WILDENBEEST (2014): "Estimation of search frictions in the British electricity market," *Journal of Industrial Economics*, 62(4), 555–590.

GOLDFARB, AVI, AND CATHERINE TUCKER (2019): "Digital economics," *Journal of Economic Literature*, 57(1), 3–43.

GORODNICHENKO, YURIY, VIACHESLAV SHEREMIROV, AND OLEKSANDR TALAVERA (2018): "Price setting in online markets: Does IT click?," *Journal of the European Economic Association*, 16(6), 1764–1811.

HONG, HAN, AND MATTHEW SHUM (2006): "Using price distributions to estimate search costs," *RAND Journal of Economics*, 37(2), 257–275.

HONKA, ELISABETH (2014): "Quantifying search and switching costs in the US auto insurance industry," *RAND Journal of Economics*, 45(4), 847–884.

HORTAÇSU, ALI, AND CHAD SYVERSON (2004): "Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds," *Quarterly Journal of Economics*, 119(2), 403–456.

HORTAÇSU, ALI, SEYED ALI MADANIZADEH, AND STEVEN PULLER (2017): "Power to choose? An analysis of consumer inertia in the residential electricity market," *American Economic Journal: Economic Policy*, 9(4), 192–226.

JOLIVET, GRÉGORY, AND HÉLÈNE TURON (2019): "Consumer search costs and preferences on the Internet," *Review of Economic Studies*, 86(3), 1258–1300.

KARLE, HEIKO, HEINER SCHUMACHER, AND RUNE VØLUND (2022): "Consumer loss aversion and scale-dependent psychological switching costs," *Games and Economic Behavior*, forthcoming.

KŐSZEGI, BOTOND, AND ADAM SZEIDL (2013): "A model of focusing in economic choice," *Quarterly Journal of Economics*, 128(1), 53–104.

KOGUT, CARL (1990): "Consumer search behavior and sunk costs," *Journal of Economic Behavior and Organization*, 14(3), 381–392.

KOULAYEV, SERGEI (2014): "Search for differentiated products: Identification and estimation," *RAND Journal of Economics*, 45(3), 553–575.

MCCALL, J. J. (1970): "Economics of information and job search," *Quarterly Journal of Economics*, 84(1), 113–126.

MORAGA-GONZÁLEZ, JOSÉ LUIS, ZSOLT SÁNDOR, AND MATTHIJS WILDENBREEST (2013): "Semi-nonparametric estimation of consumer search costs," *Journal of Applied Econometrics*, 28(7), 1205–1223.

ORLOV, EUGENE (2011): "How does the internet in influence price dispersion? Evidence from the airline industry," *Journal of Industrial Economics*, 59(1), 21–37.

RABIN, MATTHEW (2000): "Risk aversion and expected-utility theory: A calibration theorem," *Econometrica*, 68(5), 1281–1292.

RONAYNE, DAVID, DANIEL SGROI, AND ANTHONY TUCKWELL (2021): "Evaluating the sunk cost effect," *Journal of Economic Behavior and Organization*, 186, 318–327.

SCHUNK, DANIEL, AND JOACHIM WINTER (2009): "The relationship between risk attitudes and heuristics in search tasks: A laboratory experiment," *Journal of Economic Behavior and Organization*, 71, 347–360.

SHAH, ANUJ, ELDAR SHAFIR, AND SENDHIL MULLAINATHAN (2015): "Scarcity frames value," *Psychological Science*, 26, 402–412.

SNOWBERG, ERIK, AND LEEAT YARIV (2021): "Testing the waters: Behavior across participant pools," *American Economic Review*, 111(2), 687–719.

SOMERVILLE, JASON (2022): "Range-dependent attribute weighting in consumer choice: An experimental test," *Econometrica*, 90(2), 799–830.

SONNEMANS, JOEP (1998): "Strategies of search," *Journal of Economic Behavior and Organization*, 35(3), 309–332.

STAHL, DALE (1998): "Oligopolistic pricing with sequential consumer search," *American Economic Review*, 79(4), 700–712.

STIGLER, GEORGE (1961): "The economics of information," *Journal of Political Economy*, 69(3), 213–225.

THALER, RICHARD (1980): "Toward a positive theory of consumer choice," *Journal of Economic Behavior and Organization*, 1(1), 39–60.

TVERSKY, AMOS, AND DANIEL KAHNEMAN (1981): "The framing of decisions and the psychology of choice," *Science*, 211, 453–458.

URSU, RALUCA, QIANYUN ZHANG, AND ELISABETH HONKA (2022): "Search gaps and consumer fatigue," *Marketing Science*, forthcoming.

A Appendix

A.1 Proof of Proposition 1

Suppose the decision-maker exhibits diminishing sensitivity of degree γ. We define $rz = r_\gamma(z)$ so that we can write the indifference condition as

$$c = \int_a^r (v^{ds}(rz, F) - v^{ds}(pz, F)) f(p) dp. \tag{25}$$

Using implicit differentiation, we obtain

$$\frac{dr}{dz} = -\frac{r}{z} + \frac{r^\gamma}{z} \frac{1}{F(r)} \int_a^r p^{1-\gamma} f(p) dp. \tag{26}$$

This expression is zero for $\gamma = 1$ and strictly negative for $\gamma < 1$. From this the first statement follows directly. Next, we calculate that

$$\frac{\partial}{\partial \gamma} \left[\frac{dr}{dz} \right] = \frac{r^\gamma}{z} \frac{1}{F(r)} \int_a^r p^{1-\gamma} [\ln r - \ln p] f(p) dp. \tag{27}$$

Since we have $r \geq p$ this expression is strictly positive, which implies the second statement. We show that the two statements also hold if the decision-maker exhibits relative thinking of degree ρ. We define $rz = r_\rho(z)$ and write the indifference condition as

$$c = \int_a^r (v^{rt}(rz, F) - v^{rt}(pz, F)) f(p) dp. \tag{28}$$

from which we obtain

$$\frac{dr}{dz} = -\frac{1-\rho}{z} \frac{1}{F(r)} \int_a^r (r - p) f(p) dp. \tag{29}$$

This expression is zero for $\rho = 1$ and strictly negative for $\rho < 1$, which shows the first statement for relative thinking. Further, we obtain

$$\frac{\partial}{\partial \rho} \left[\frac{dr}{dz} \right] = \frac{1}{z} \frac{1}{F(r)} \int_a^r (r - p) f(p) dp. \tag{30}$$

Since this expression is strictly positive, the second statement also holds for relative thinking.

A.2 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.

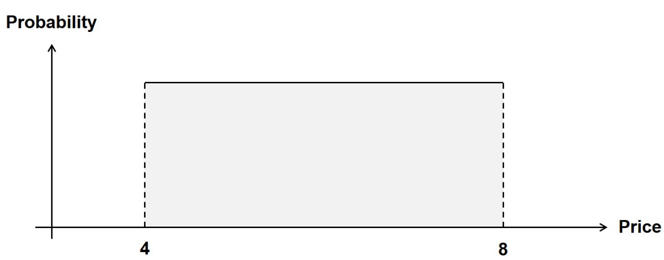
You can simply buy product A for 8 USD. **You do not need to do anything else for this. All the earnings will be paid automatically.**

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.3 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 in order to contrast the implications of sequential and non-sequential search.[18]

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

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 relationship.*

Table A1 summarizes the results of all tests. For Test 1, we find that 87.7 percent of AMT workers and 59.4 percent of student subjects indeed purchase from the last sampled shop or search all 100 shops (six student subjects did the latter). Importantly, the probability of buying from the last sampled shop is much larger than the probability of buying from any given previously sampled shop (one-sided t-tests, p-values < 0.001). In Table A2, we further illustrate these differences by considering subject subgroups with a certain number of searches.

With respect to Test 2, we find that those subjects who search exactly once find on average a significantly lower price at the first shop than subjects who search more than once. The differences are significant for both AMT workers (one-sided t-tests, p-values < 0.014) and student subjects (one-sided t-tests, p-values < 0.001). This is also confirmed in a linear probability regression model, see Column 1 and Column 2 of Table A3 and Table A4. Finally, for Test 3, we find that, at any shop, the probability of continuing search increases significantly in the observed price. Table A1 shows the average increase in the probability of continuing search when the price at the current shop is raised by one USD/Euro. These results originate from a linear probability regression model, see Column 3 and Column 4 of Table A3 and Table

[18] 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.

A4. The corresponding coefficients are all significant at the 1-percent level. We conclude that behavior in our experiment is roughly consistent with sequential search and inconsistent with non-sequential search.

Table A1: Sequential versus Non-Sequential Search

	Panel A: AMT workers		*Panel B: Student Subjects*	
Test 1 (Recall)				
share purchase from last sampled shop or search all shops	87.7%		59.4%	
av. purchase prob. for previously sampled shop	5.9%		4.9%	
Test 2 (Price Dependence I)				
price at first shop	one search	multiple search	one search	multiple search
$S\,0.5/S\,1.0$	2.84	3.20	4.76	6.07
$S\,1.5/S\,3.0$	8.29	9.81	13.68	18.98
$S\,2.5/S\,5.0$	14.73	15.98	23.24	31.22
$S\,3.5/S\,7.0$	20.61	22.54	30.60	42.26
Test 3 (Price Dependence II)				
change in prob. continuing search	one USD price increase at current shop		one Euro price increase at current shop	
$S\,0.5/S\,1.0$	23.1%		7.4%	
$S\,1.5/S\,3.0$	7.9%		1.8%	
$S\,2.5/S\,5.0$	5.1%		1.3%	
$S\,3.5/S\,7.0$	3.4%		0.8%	

Notes: The results for Test 3 originate from a linear probability regression model (Column 3 and Column 4 of Table A4 and Table A3).

Table A2: Search and Recall

Number Searches	Observations	Share	Share Last Shop	Av. Probability of Recall
		Panel A: 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%
		Panel B: 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%

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 A3: 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)
β_0	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 *** $p < 0.01$.

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)
β_0	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 *** $p < 0.01$.

A.4 Individual Expected Search Costs

In our ordered probit model from Subsection 5.2, we assume that the log of search costs, $\ln c_i$, is normally distributed for all subjects $i \in \{1, ..., I\}$. The probability density function and cumulative distribution function of $\ln c_i$ are given by

$$\phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right) \text{ and } \Phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right),$$

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

$$\phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right)\frac{1}{c_i} \text{ and } \Phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right).$$

The (unconditional) expected value of search costs equals

$$\mathbb{E}[c_i] = \exp\left(x_i\beta + \frac{\sigma^2}{2}\right).$$

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

$$\mathbb{E}[c_i \mid c(p_i^1, \gamma) \leq c_i < c(p_i^2, \gamma)] = \int_{c(p_i^1,\gamma)}^{c(p_i^2,\gamma)} \frac{c_i\phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right)\frac{1}{c_i}}{\Phi\left(\frac{\ln c(p_i^2,\gamma) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma) - x_i\beta}{\sigma}\right)} dc_i.$$

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

$$\mathbb{E}[c_i \mid c(p_i^1, \gamma) \leq c_i < c(p_i^2, \gamma)] = \mathbb{E}[c_i] \cdot \frac{\Phi\left(\frac{\ln c(p_i^2,\gamma) - (x_i\beta + \sigma^2)}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma) - (x_i\beta + \sigma^2)}{\sigma}\right)}{\Phi\left(\frac{\ln c(p_i^2,\gamma) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma) - x_i\beta}{\sigma}\right)}.$$

A.5 Robustness Checks $R1$ and $R2$

In the robustness check $R1$, we updated the information provided in the invitation on AMT for our HIT. We first show the invitation of the baseline study and then the invitation of the first robustness check. Next, we show the precise wording of the comprehension question in robustness check $R2$.

A.5.1 AMT Invitation Baseline Study

Title:

Scientific study, survey (USD 1, 5-10 minutes, option to earn bonus in additional part (online shopping experiment)).

Description:

Short survey and online shopping experiment.

Procedures:

Scientific Study, survey (USD 1, 5-10 minutes, option to earn bonus in additional part (online shopping experiment)).

This is a scientific study conducted by researchers from Frankfurt School of Finance & Management, KU Leuven, and the University of Innsbruck. Your Worker ID will be retrieved automatically when you click the link to start the project. It will only be used for assigning the payment to the right account and to control that you have not participated in this HIT before. On the last page of the survey, you will receive a personalized completion code. Please copy and paste this completion code in the box below so that we can verify that you have completed the survey.

Please click on the link below in order to start.

Make sure to leave this window open as you complete the project.

A.5.2 AMT Invitation in Robustness Check $R1$

Title:

Scientific study, survey, experiment (USD 1 for sure; you can work on the experiment as long as you like to earn more than USD 1).

Description:

There are two parts to this HIT. First, a short survey for which you get USD 1. Second, you can work on an online shopping experiment as long as you like. For the experiment, you can earn more money (will be paid as a bonus). Details follow in the first part.

Procedures:

Scientific survey and online shopping experiment (USD 1 for completing the survey; you can work on the experiment as long as you like and earn more money).

This is a scientific study conducted by researchers from Frankfurt School of Finance & Management, KU Leuven, and the University of Innsbruck.

There are two parts to this HIT. First, a short survey for which you get USD 1. Second, you can work on an online shopping experiment as long as you like. For the experiment, you can earn more money (paid as a bonus). You will learn in the first part how the second part works, including how much additional money you can earn.

Your Worker ID will be retrieved automatically when you click the link to start the project. It will only be used for assigning the payment to the right account and to control that you have not participated in this HIT before. On the last page of the survey, you will receive a personalized completion code. Please copy and paste this completion code in the box below so that we can verify that you have completed the survey.

Please click on the link below in order to start.

Make sure to leave this window open as you complete the project.

A.5.3 AMT Comprehension Question in Robustness Check $R2$

At the end of the instructions to Part 2 of our study (after Screen 5), we asked the following comprehension question:

To see whether we explained everything clearly, we will now ask you to answer the following question: Suppose that, after searching for the lowest price, you buy product A at a price of [0.7 $\times$ highest price] USD. What will be your bonus? [Textfield] USD

In case of a wrong answer, we provided the correct answer and an explanation.

A.6 Instructions for Robustness Check $R3$

Instructions for Part 2, Screen 1

The second part of the study is about buying two products. We call them "Product A" and "Product B."

Your budget for product A is 4 USD. If you buy product A at price P, you additionally earn 4 USD minus the price, that is 4 - P USD. Your budget for product B is 28 USD. If you buy product B at price P*, you additionally earn 28 USD minus the price, that is 28 - P* USD. The earnings from the two transactions will be paid as a bonus in MTurk.

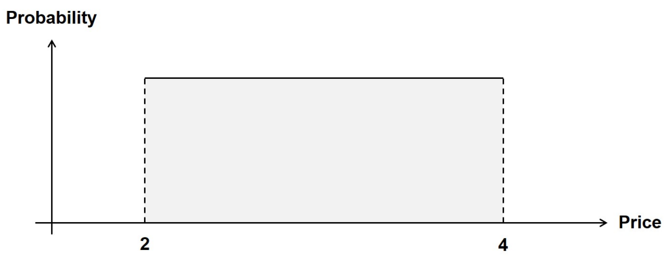
You can simply buy product A for 4 USD and product B for 28 USD. **You do not need to do anything else for this. All the earnings will be paid automatically.**

Alternatively, you can search for a lower price for product A and product B 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 and access to up to 100 shops that offer product B. The prices in each product A online shop vary between 2 and 4 USD. The following graph shows the probability distribution over all possible prices in each product A online shop. All prices between 2 and 4 USD are equally probable.



The prices in each product B online shop vary between 14 and 28 USD. All prices between 14 and 28 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 a product 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 searching for a product 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 and product B only once. As soon as you click "Buy", you purchase the corresponding product at the price of this online shop. After buying product A and product B the study is over.

Instructions for Part 2, Screen 5

If you do nothing, you automatically buy product A at a price of 4 USD and product B at a price of 28 USD. We then pay you a bonus of 0 USD for the second part of the study.

If you buy product A at price P and product B at price P*, we pay you a bonus of

$$(4 - P) + (28 - P^*) \text{ USD.}$$

If you visit some product A online shops but do not buy product A from any of them, you will automatically buy product A at the price of 4 USD. If you visit some product B online shops but do not buy product B from any of them, you will automatically buy product B at the price of 28 USD.

Instructions for Part 2, Screen 6

Before continuing with the second part and searching for prices of product A and product B, 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 and product B. 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.7 Additional Tables

Table A5: Search Model with/without Relative Thinking (ρ fixed)

	(1)	(2)	(3)	(4)
	Panel A: AMT Workers		*Panel B: Student Subjects*	
$S0.5/S1.0$	0.192***	0.424***	0.131***	0.247***
	(0.031)	(0.069)	(0.027)	(0.050)
$S1.5/S3.0$	0.198***	1.528***	0.154***	0.481***
(0.031)	(0.237)	(0.032)	(0.101)	
$S2.5/S5.0$	0.207***	2.860***	0.140***	0.551***
	(0.032)	(0.444)	(0.029)	(0.113)
$S3.5/S7.0$	0.187***	3.794***	0.126***	0.579***
	(0.027)	(0.558)	(0.027)	(0.124)
$\tilde{\sigma}$	0.512***	4.486***	0.569***	1.826***
	(0.084)	(0.739)	(0.139)	(0.447)
ρ	1.141	0.000	0.457	0.000
Controls	No	No	No	No
Observations	528	528	490	490

Notes: Separate search costs per treatment, based on ordered probit (17) with fixed ρ at the estimated values from Table 7 and at zero (as in Table 4). The scale dummies and $\tilde{\sigma}$ are transformed estimates reflecting average search costs and the standard deviation of search costs, respectively; $\tilde{\beta}_j = \exp(\beta_j + \frac{\sigma^2}{2})$ with $j \in \{1, ..., 4\}$ indicating the number of the scale dummy ordered by size; $\tilde{\sigma} = \sqrt{\exp(2\bar{x}\beta + \sigma^2)(\exp(\sigma^2) - 1)}$, where $\bar{x} = \frac{1}{I}\sum_{i=1}^{I} x_i$. Standard errors are in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A6: Descriptive Statistics Across Treatments, all subjects

Treatment	$S0.5/S1.0$	$S1.5/S3.0$	$S2.5/S5.0$	$S3.5/S7.0$	One-way ANOVA p-value
		Panel A: 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	
		Panel B: 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
Economics	0.30	0.29	0.24	0.33	0.398
Observations	148	146	143	144	

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 A7: Descriptive Statistics Across Treatments, searchers only

Treatment	$S0.5/S1.0$	$S1.5/S3.0$	$S2.5/S5.0$	$S3.5/S7.0$	One-way ANOVA p-value
	Panel A: 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	
	Panel B: 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	0.32	0.30	0.25	0.34	0.495
Observations	126	121	124	119	

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 A8: Comparison of Search Cost Measures: Predicted and Direct Search Costs

	(1)	(2)
Log(direct search costs)	0.241***	0.226***
	(0.062)	(0.062)
Age		-0.003
		(0.004)
Gender (share females)		-0.114
		(0.096)
Willingness to take risk		0.065***
		(0.020)
CRT score		-0.058
		(0.042)
β_0	-1.942***	-2.094***
	(0.132)	(0.260)
Observations	512	512
R^2	0.0358	0.0742

Notes: OLS regressions. The dependent variable is the log of the model's predicted 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 A9: Results from Robustness Checks $R1$ and $R2$

	Panel A: Robustness 1		*Panel B: Robustness 2*	
Descriptive Statistics	All Subjects	Searchers	All Subjects	Searchers
Age	35.8 (10.1)	36.0 (10.5)	40.4 (12.4)	40.3 (12.2)
Gender (share females)	0.42	0.41	0.39	0.36
Willingness to take risk	6.7 (2.6)	6.6 (2.7)	5.8 (2.7)	5.6 (2.7)
CRT score	1.3 (1.2)	1.5 (1.1)	1.6 (1.2)	1.8 (1.2)
Average hourly earnings	9.7 (11.4)	10.4 (11.7)	7.1 (5.8)	7.0 (5.7)
Average hours per week	25.5 (17.1)	25.0 (16.7)	21.1 (15.1)	19.4 (13.6)
Observations	304	232	306	246
Average Search Behavior	Mean No. Searches if search	Median No. Searches if search	Mean No. Searches if search	Median No. Searches if search
$R1-S0.5/R2-S0.5$	1.9 (1.9)	1	2.3 (2.7)	1
$R1-S3.5/R2-S3.5$	3.3 (5.2)	1	3.1 (4.6)	1
	Share Searchers	Gain Share if search	Share Searchers	Gain Share if search
$R1-S0.5/R2-S0.5$	0.78	0.59	0.82	0.66
$R1-S3.5/R2-S3.5$	0.74	0.63	0.79	0.69
Search Time	Mean Search Duration	Median Search Duration	Mean Search Duration	Median Search Duration
$R1-S0.5/R2-S0.5$	103.7 (89.6)	79.5	77.6 (48.2)	65.75
$R1-S3.5/R2-S3.5$	87.3 (69.4)	72	86.4 (63.0)	71
Direct Search Costs	(1)		(2)	
$R1/R2$	0.33 (0.63)		0.17 (0.30)	

Table A10: Results from Robustness Checks $R1$ and $R2$ (continuation)

	Panel A: Robustness 1		*Panel B: Robustness 2*	
Search Cost Estimates, $\gamma = \rho = 0$	(1)	(2)	(3)	(4)
$R1 - S0.5/R2 - S0.5$		0.603^{***}		0.591^{***}
		(0.086)		(0.105)
$R1 - S3.5/R2 - S3.5$		3.063^{***}		3.071^{***}
		(0.466)		(0.503)
$\tilde{\beta}_0$	1.641^{***}		1.852^{***}	
	(0.242)		(0.324)	
$\tilde{\sigma}$	4.458^{***}	2.434^{***}	7.079^{***}	3.713^{***}
	(1.134)	(0.479)	(2.166)	(0.908)
γ	0.000	0.000	0.000	0.000
Observations	232	232	246	246
Search Cost Estimates, flexible γ/ρ	(1)	(2)	(3)	(4)
$\tilde{\beta}_0$	0.249^{***}	0.338^{***}	0.272^{***}	0.329^{***}
	(0.052)	(0.063)	(0.071)	(0.076)
$\tilde{\sigma}$	0.404^{***}	0.640^{***}	0.631^{***}	0.876^{***}
	(0.108)	(0.157)	(0.215)	(0.267)
γ	0.793^{***}		0.757^{***}	
	(0.088)		(0.103)	
ρ		0.835^{***}		0.847^{***}
		(0.094)		(0.106)
Observations	232	232	246	246

Notes: Upper panel: Search cost estimates with $\gamma = \rho = 0$, same regressions as in Table 4 (without controls). Lower panel: Search cost estimates with flexible γ (Columns 1 and 3) and ρ (Columns 2 and 4), same regressions as in Table 5 and 7 (without controls), respectively. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A11: Results from Robustness Check $R3$

Descriptive Statistics	All Subjects	Searchers
Age	40.7 (11.2)	41.4 (11.3)
Gender (share females)	0.50	0.51
Willingness to take risk	7.6 (2.1)	7.6 (2.2)
CRT score	1.2 (1.0)	1.4 (1.0)
Average hourly earnings	7.5 (10.1)	7.4 (10.6)
Average hours per week	26.5 (15.5)	28.2 (15.5)
Observations	191	138
Average Search Behavior	**Mean No. Searches if search**	**Median No. Searches if search**
$R3 - S0.5$	1.3 (1.4)	1
$R3 - S3.5$	1.7 (3.0)	1
	Share Searchers	**Gain Share if search**
$R3 - S0.5$	0.66	0.54
$R3 - S3.5$	0.66	0.56
Search Time	**Mean Search Duration**	**Median Search Duration**
$R3 - S0.5$	87.7 (67.9)	68
$R3 - S3.5$	82.4 (56.7)	65
Direct Search Costs	(1)	
$R3$	0.18 (0.29)	

Table A12: Results from Robustness Check $R3$ (continuation)

Search Cost Estimates, $\gamma = \rho = 0$	(1)	(2)
$R3 - S0.5$		0.611
		(0.052)
$R3 - S3.5$		3.874
		(0.338)
$\tilde{\beta}_0$	2.001	
	(0.212)	
$\tilde{\sigma}$	3.470	1.379
	(0.640)	(0.153)
γ	0.000	0.000
Observations	245	245

Search Cost Estimates, flexible γ/ρ	(1)	(2)
$\tilde{\beta}_0$	0.216	0.316
	(0.027)	(0.037)
$\tilde{\sigma}$	0.170	0.287
	(0.027)	(0.043)
γ	0.931	
	(0.055)	
ρ		0.949
		(0.061)
Observations	245	245

Notes: Upper panel: Search cost estimates with $\gamma = \rho = 0$, same regressions as in Table 4 (without controls). Lower panel: Search cost estimates with flexible γ (Column 1) and ρ (Column 2), same regressions as in Table 5 and 7 (without controls), respectively. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A13: γ Estimates under (log) normal distribution and Box-Cox transformation

	(1)	(2)	(3)	(4)	(5)	(6)
		Panel A: AMT workers			*Panel B: Student Subjects*	
β_0	-2.632***	-1.373***	-0.882***	-3.374***	-2.645***	-0.953***
	(0.205)	(0.072)	(0.010)	(0.327)	(0.220)	(0.006)
σ	1.317***	0.273***	0.077***	1.672***	0.927***	0.049***
	(0.050)	(0.039)	(0.007)	(0.065)	(0.125)	0.006
γ	0.975***	1.046***	1.069***	0.415***	0.511***	0.694***
	(0.089)	(0.051)	(0.034)	(0.120)	(0.111)	(0.046)
λ	0	0.504***	1	0	0.155***	1
		(0.042)			(0.031)	
Observations	528	528	528	490	490	490

Notes: Ordered probit regressions with flexible γ and Box-Cox parameter λ on search costs; $\lambda = 0$ reflects a log-normal distribution and $\lambda = 1$ a normal distribution of search costs; β_0 and σ are the original estimates reflecting the average and standard deviation of Box-Cox transformed search costs. In Columns (2) and (5), the parameter λ is estimated through a Box-Cox transformation. Otherwise, it is given as indicated in the table. Standard errors are in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A14: ρ Estimates under (log) normal distribution and Box-Cox transformation

	(1)	(2)	(3)	(4)	(5)	(6)
		Panel A: AMT workers			*Panel B: Student Subjects*	
β_0	-2.663***	-1.364***	-0.810***	-3.433***	-2.644***	-0.930***
	(0.198)	(0.079)	(0.015)	(0.313)	(0.229)	(0.008)
σ	1.436***	0.417***	0.132***	1.703***	1.006***	0.076***
	(0.051)	(0.045)	(0.010)	(0.065)	(0.122)	(0.008)
ρ	1.141***	1.078***	1.055***	0.457***	0.498***	0.592***
	(0.097)	(0.059)	(0.037)	(0.119)	(0.111)	(0.036)
λ	0	0.432***	1	0	0.142***	1
		(0.037)			(0.03)	
Observations	528	528	528	490	490	490

Notes: Ordered probit regressions with flexible γ and Box-Cox parameter λ on search costs; $\lambda = 0$ reflects a log-normal distribution and $\lambda = 1$ a normal distribution of search costs; β_0 and σ are the original estimates reflecting the average and standard deviation of Box-Cox transformed search costs. In Columns (2) and (5), the parameter λ is estimated through a Box-Cox transformation. Otherwise, it is given as indicated in the table. Standard errors are in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.