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Search Costs and Diminishing Sensitivity

Abstract

Empirical search cost estimates tend to increase 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. Based on a standard search model, we confirm that search cost estimates indeed increase considerably in the price scale. We then modify the search model to allow for diminishing sensitivity, i.e., the tendency that people become less sensitive to price variations of fixed size when the price of the good increases. With the modified model, we find substantial degrees of diminishing sensitivity and obtain search cost estimates that are scale-independent. We show that these search cost estimates correspond well to subjects' true opportunity costs of time and that the consumer welfare loss from diminishing sensitivity can be quite substantial.

JEL-Codes: C900, D120, D830.

Keywords: consumer search, diminishing sensitivity, search costs.

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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; see Brynjolfsson and Smith (2000), Baye et al. (2004), Orlov (2011), Einav et al. (2015), Gorodnichenko et al. (2018), and Jolivet and Turon (2019). The empirical literature that estimates consumer search costs from observational data finds large average search costs in digital markets for books (Hong and Shum 2006, De los Santos et al. 2012), 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). An interesting feature of these estimates is that their size increases in the value of the transaction.[1] The resulting search costs are often difficult to reconcile with the labor input that is necessary to identify and evaluate an alternative product. For example, Hortaçsu et al. (2017) report that by investing 15 minutes into finding (and switching to) a cheaper energy provider, consumers could reduce their annual electricity costs by 100 USD.[2]

Several reasons could justify why search cost estimates increase in the price scale. More valuable products are typically also more complex. 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. Another reason may be that many consumers are pessimistic about the benefits from search and therefore spend too little effort on finding the best deal. However, we demonstrate in this paper that we obtain search cost estimates that increase in the price scale even when we keep the complexity of the product and

[1]Here is an example. For books sold at prices between 8 and 23 USD, De los Santos et al. (2012) find search costs of around 1.35 USD per search. For memory chips sold at prices between 116 and 182 USD, Moraga-González et al. (2013) find search cost per search of around 8.70 USD. For electricity contracts with prices around 260 USD, Giulietti et al. (2014) document that 50 percent of customers exhibit search costs of at least 41.6 USD per search. This pattern also generalizes to switching contracts, see Karle et al. (2021) for an overview. An alternative explanation for large search cost estimates could be publication bias (e.g., DellaVigna and Linos 2022). However, the focus of this literature is not so much on the size of the search cost estimates, but mostly on how the search cost model leverages the data. We therefore believe that publication bias cannot explain the positive relationship between search cost estimates and transaction value.

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

the search process constant, trust issues do not arise, and individuals are informed about the potential gains from search. This implies that at higher prices individuals do not fully take into account the benefits of (continued) search and therefore stop searching too early. We provide a behavioral explanation for this tendency and update a classic search model so that it generates scale-independent search cost estimates. It turns out that these scale-independent search cost estimates correspond well to individuals' opportunity costs of time. We quantify the loss in consumer welfare using the updated model and show that it can be quite substantial.

To obtain data on search and purchase prices in an environment where the price scale varies while everything else remains the same, we conduct an online search experiment. Its setting closely resembles the framework of the random sequential search model (e.g., McCall 1970, Stahl 1989), which has been used frequently in the empirical search cost literature.[3] Subjects can search for the lowest price of a (hypothetical) homogeneous product in up to 100 online shops. Their payoff in the experiment equals the price savings they realize. The price distribution is exogenously given and the same for each shop. Our treatment variation is the price scale. It varies by a factor of seven between the treatment with the lowest and the treatment with the highest price scale. The physical search costs – entering a 16-digit code at each online shop – are the same in all treatments. When deciding about search, subjects have complete information about the price distribution and the effort required to obtain a price quote. They also have several days to complete their price search. We conduct the experiment both with student subjects and online workers on Amazon Mechanical Turk (AMT). To estimate search costs, we use the random sequential search model. It implies that the 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.

In line with what is suggested by empirical studies, we find that estimated search costs indeed increase in the price scale. In the student sample, raising the price scale by a factor of seven increases the average estimated search costs per search by 134 percent. The average search costs in the highest scale treatment are 0.58 Euro per search and each search takes on average around 60 seconds, i.e., we obtain an implied average hourly reservation wage of around 35 Euro. In the AMT worker sample, raising the price scale by the same factor increases the average estimated search costs by even 795 percent. The average search costs in the highest scale treatment are 3.79 USD per search, and each search takes on average 85 seconds. This implies an average hourly reservation wage of around 161 USD. These results indicate that the standard search model most likely does not only capture subjects' time and hassle costs of search and needs to be updated to mitigate the apparent contradictions.

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

To avoid search cost estimates that increase in the price scale, we integrate "diminishing sensitivity" into the random sequential search model. Diminishing sensitivity implies that a certain amount of price savings appears large to a consumer when the price scale is small, but small when the price scale is large. We propose diminishing sensitivity as the behavioral mechanism behind our results as it has been suggested repeatedly in the behavioral economics and psychological literature. First, diminishing sensitivity is, in varying configurations, an important feature of several non-standard preference models like reference-dependent loss aversion (Kőszegi and Rabin 2016) and preferences with salience distortions (Bordalo et al. 2013). In addition, the implications of diminishing sensitivity for search are similar to those of relative thinking preferences as introduced by Bushong et al. (2021), which we consider in an extension.[4] Second, diminishing sensitivity is also consistent with the Weber-Fechner law of psychophysics (Weber 1834, and Fechner 1860), which proposes that the intensity of a sensation increases linearly only in the logarithm of the energy that creates this sensation.[5] Third, diminishing sensitivity can explain choices in the famous "jacket-calculator vignette" explored by Thaler (1980), Tversky and Kahneman (1981), Azar (2011), and Shah et al. (2015). Thaler's (1980) version of this vignette goes as follows:

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

Typical answers to these questions imply that people are more willing to realize the savings of 5 USD in the first situation than in the second situation. To obtain a search model that takes this behavioral tendency into account, we update the consumer's utility function from $u - p$ to $u - v(p)$, where u is the utility of the product, p the price that the consumer pays for the product, and v a concave function. To estimate the degree of diminishing sensitivity, we assume that v is a power utility function with constant γ that captures the degree of diminishing sensitivity.[6] For $\gamma = 0$, the model is identical to the standard sequential search model. For $\gamma = 1$, the search

[4] See Subsection 7.5.

[5] Thaler (1980) refers to the Weber-Fechner law in the context of search. Recent theoretical as well as experimental work in economics finds connections to the Weber-Fechner law, e.g., Adriani and Sonderegger (2020) or Caplin et al. (2020). It is also found in data related to vision, haptics, audition, and – importantly – the mental representation of numbers (Nieder et al. 2002).

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

model would predict that search effort is independent of the price scale. This case would correspond to the Weber-Fechner law from psychophysics. We can use our data to jointly estimate search costs and the degree of diminishing sensitivity γ in the population. For this, we exploit the fact that search requires the same effort in all treatments.

We update our ordered probit framework to jointly estimate search costs per search and the degree of diminishing sensitivity in the subject population. We find a degree of diminishing sensitivity of $\gamma = 0.42$ among student subjects and of $\gamma = 0.98$ among AMT workers. These values roughly equalize the search cost estimates in all treatments, and they also almost equalize search costs among student subjects and AMT workers. The resulting average search costs are 0.14 Euro per search in the student subject pool and 0.17 USD per search for AMT workers. These results imply that for expensive items standard search cost estimates partly reflect the price scale and not actual time and hassle costs.

Using the updated search model and our search cost estimates, we can assess subjects' welfare loss in our setting that is due to diminishing sensitivity. If an individual searches less, she economizes on search costs, but pays a higher price in expectation. For small degrees of diminishing sensitivity – values around $\gamma = 0.40$ – the welfare loss is only a few percentage points of the total gains from search. However, for the AMT workers' degree of diminishing sensitivity – values around $\gamma = 1.00$ – the welfare loss can be substantial, up to 40 percent of the total gains from search. In particular, the welfare loss from diminishing sensitivity is large for individuals with relatively high search costs.

The data from the AMT workers further allow us to evaluate whether the search cost estimates from the modified model capture the real time and hassle costs of search in our setting. The AMT workers in our sample work on average 20 hours per week on AMT. Thus, they face a clear trade-off between searching and working in other jobs. We elicit from each AMT worker how much they earn on average in one hour by working on AMT. Additionally, we know for each AMT worker how much time she needs on average to obtain a price quote. Combining these two measures yields us a direct search cost measure for each individual AMT worker. The average value of direct search costs is 0.16 USD and hence remarkably close to the average search costs estimates of 0.17 USD from the modified model. We also find a significant positive correlation between an individual AMT worker's estimated search costs and her opportunity costs of time. These results suggest that, on average, the search cost estimates from the modified model correspond to subjects' true time and hassle costs of search.

Related Literature. The paper contributes to 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 largely uses observational data. Important contributions on price search in online settings are 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. Moreover, the AMT setting allows us to derive a direct search cost measure to which we can compare the search cost estimates from the modified model.

There is also a large experimental literature on consumer search and search markets; see, e.g., Kogut (1990), Sonnemans (1998), Schunk and Winter (2009), 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. In contrast, we consider "real" hassle and time costs since subjects need to insert a 16-digit code to obtain a price quote. This allows us to study how the relationship between physical search costs and monetary gains of search changes in the price scale of products. Importantly, we consider an online search environment and give subjects several days for searching. The experimental setting is therefore close to a generic online search environment.

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

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 diminishing sensitivity. In Section 3, we describe our experimental design. In Section 4, we characterize our subject pool, average search behavior, and test to what extent search behavior conforms to sequential and non-sequential search. In Section 5, we estimate search costs in our online setting and the degree of diminishing sensitivity. In Section 6, we compare our search cost estimates with a direct measure of search costs that is derived from average hourly earnings and search duration. In Section 7, we present a number of robustness checks and extensions. Section 8 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 Diminishing Sensitivity

We consider a standard utility framework where the indirect utility function captures both utility from money and utility from leisure. Combining this indirect utility function with a standard search model – random sequential search – generates the classic indifference condition for optimal search under this model. We then examine how diminishing sensitivity with respect to prices affects this indifference condition and hence search behavior.

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

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

Only this shape of the indirect utility function is consistent with a standard utility framework[7] when p is small relative to the decision-maker's total budget, and the time spent on search is small relative to her total available time.

There is a (large) finite number of firms that offer the good at varying prices. Each firm chooses its price p according to the distribution $F(p)$ with support on $[a, b]$, where $b > a > 0$,

[7]This utility framework would be as follows. A decision-maker has a budget of y that she can spend on a good g at price p for which she has unit demand, and on a numeraire $x \geq 0$ at normalized price one. Her budget constraint is $pg + x \leq y$. She also can spend time on search for a lower price of good g. Let p be very small relative to y and that the disutility from search is separable from the utility from consumption. The decision-maker's utility is given by $u(x, g) - L$, where the utility function u is continuously differentiable and strictly increasing in the first argument. We assume $u(x, 1) > u(x', 0)$ for any x, x' in the decision-maker's budget set. From a linear Taylor-approximation we 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 $u_1(y, 1) = 1$.

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

We consider a classic search paradigm from the literature, random sequential search. Under this paradigm, the decision-maker chooses after each search whether to purchase the good at the lowest price discovered so far or to conduct one more search. The 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. We can calculate the value of the indirect utility function (1) at the optimal search strategy as

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

where r is defined 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 diminishing sensitivity, we briefly comment on an alternative search paradigm that is frequently considered in the theoretical and empirical literature, i.e., non-sequential search (or "fixed sample size search"). This search strategy has been introduced by Burdett and Judd (1983). Non-sequential search means that the decision-maker chooses the number n of price 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 Appendix A.3, we show that search behavior in our experiment is roughly consistent with sequential and inconsistent with non-sequential search. Therefore, we focus on sequential search.

2.2 Diminishing Sensitivity

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

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

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

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

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

The power utility function has been frequently used to model expected utility risk preferences with constant relative risk aversion. Therefore, it is important to point out that diminishing sensitivity in our framework is unrelated to risk preferences. We use the power utility function mainly for tractability reasons.

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

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

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

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

it follows that, at a reservation price of zr, the expected payoff from one more search is the same at any scale z. The optimal reservation price is therefore equal to zr. The probability that she conducts a certain number of searches is then the same under any scale. This result does not depend on the distribution over prices $F(p)$. In contrast, the expected number of searches would increase in the scale under standard preferences, i.e., when $v(p) = p$.

To describe these findings formally, we introduce the following notation. Denote by r_γ the reservation price at search costs c and distribution of prices $F(p)$ on the interval $[a, b]$ when the decision-maker exhibits the degree of diminishing sensitivity γ. It is defined by equation (6), after substituting the power utility function (5). We are interested in how this value changes when prices are scaled by a factor z. Denote by $r_\gamma(z)$ the corresponding reservation price. The value $\frac{r_\gamma(z)}{z}$ is a relative reservation price that indicates to what extent the decision-maker searches more, in expectation, when the price scale increases. We obtain the following results (their proof is in Appendix A.1).

Proposition 1 (Expected Search Behavior)**.** *Let the distribution F over prices on the interval $[a, b]$ be given. Consider a decision-maker who exhibits positive search costs c and a degree of diminishing sensitivity γ. Suppose that c is small enough such that the decision-maker's reservation price is smaller than b at all values $\gamma \in [0, 1]$.*

(i) If $\gamma < 1$, the relative reservation price $\frac{r_\gamma(z)}{z}$ is strictly decreasing in z. In this case, the expected number of searches increases if prices are scaled up by a factor of $z > 1$.

(ii) If $\gamma = 1$, the relative reservation price $\frac{r_\gamma(z)}{z}$ is constant in z. In this case, the expected number of searches remains the same if prices are scaled up by a factor of $z > 1$.

(iii) The change in the relative reservation price $\frac{\partial}{\partial z}\left[\frac{r_\gamma(z)}{z}\right]$ strictly increases in γ, i.e., the extent to which the expected number of searches increases in z is reduced as the degree of diminishing sensitivity increases.

3 Experimental Design and Procedures

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

In Part 2, subjects have to purchase a hypothetical product[8], 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. The "copy and paste" option 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 price of the shop. 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 without re-entering the code, so recall is essentially costless. In Part 1 of the experiment, we inform subjects about this procedure, and we ask them to enter an example code. Thus, they know in advance the physical costs of price search.

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

[8] 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.

of the University of Innsbruck.

Student Subject Pool. Our first 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.

AMT Subject Pool. Our second 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.[9] 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.

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 two Euro for student subjects in treatment $S1.0$ and one USD for AMT workers in treatment $S0.5$, 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).

[9] 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 student subjects and AMT workers. In Subsection 4.2, we examine some basic statistics on search effort in our setting. Additionally, we show in Appendix A.3 that subjects' search behavior is roughly in line with sequential, but not with non-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."

Overall, 84.3 percent of all student subjects and also 84.3 percent of all AMT workers in our sample are searchers.[10] 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. There are no significant differences in personal characteristics between searchers and non-searchers. The AMT workers' average age is 39.6 years and 44 percent of them are female. Their average education is relatively high. Around a quarter indicates to have a high school degree as highest educational degree, and three quarters indicate to have a Bachelor's or a higher degree. Again, there are no significant differences in these demographic variables between searchers and non-searchers.

For both student subjects and AMT workers 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. Student subjects' average willingness to take risk is 5.4, for AMT workers this value is 5.9. The average CRT-score of both groups is also rather similar, 2.1 for student subjects and 1.7 for AMT workers (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).

[10] 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 Euro/USD. These are 9 student subjects and 14 AMT workers.

Table 1: Descriptive Statistics – Demographic Variables

	All Subjects	Searchers
	Panel A: Student Subjects	
Age	23.5 (3.2)	23.4 (3.0)
Gender (share females)	0.62	0.61
Willingness to take risk	5.4 (2.1)	5.4 (2.1)
CRT score	2.1 (1.1)	2.1 (1.1)
Study Field		
Economics	29.1%	30.0%
Law	5.7%	6.1%
Science	17.2%	16.7%
Humanities	22.6%	21.6%
Medical Science	15.3%	15.1%
Other	10.2%	10.4%
Observations	581	490
	Panel B: AMT Workers	
Age	39.6 (11.7)	39.9 (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

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).

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 A7 and A8 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 Average Search Behavior

We provide a brief overview of search behavior in our experiment. Recall from Proposition 1 that, under a high degree of diminishing sensitivity, $\gamma \approx 1$, search behavior should be the same in all treatments. In contrast, if subjects' degree of diminishing sensitivity is sufficiently small, we should observe that the average number of searches increases significantly in the price scale. Table 2 summarizes subjects' average search behavior in our experiment. It shows the price scale for each treatment, the share of searchers, the average number of searches (provided that at least one search has been conducted), the median number of searches among searchers, and the average share of gains realized for those who conduct at least one search, that is, the value $(b - \bar{p})/(b - a)$ where $\bar{p}$ is the average price paid by searchers.

Among student subjects, the share of searchers does not vary significantly between the different treatments (one-way ANOVA, p-value = 0.747). The number of searches among those who search increases from around 7 in $S1.0$ to 11.5 in $S7.0$. Although this increase is statistically significant (Jonckheere-Terpstra test, p-value = 0.006), this is partly driven by a small share of subjects who search a lot of shops. Six subjects search all 100 shops, two of them in $S3.0$, one in $S5.0$, and three in $S7.0$. Accordingly, the median number of searches only increases from 5 in $S1.0$ to 6 in $S7.0$. The average share of gains realized increases from 87 percent in $S1.0$ to 93 percent in $S7.0$ (Jonckheere-Terpstra test, p-value < 0.001). Hence, the amount of search slightly increases in scale, which suggests a degree of diminishing sensitivity γ below one (according to Proposition 1).

Among AMT workers, the share of searchers again does not vary significantly between treatments (one-way ANOVA, p-value = 0.931). The number of searches among those who search neither increases nor decreases between $S0.5$ and $S3.5$ (Jonckheere-Terpstra test, p-value = 0.575). Surprisingly, the average share gains realized slightly decreases, from 68

Table 2: Descriptive Statistics – Search Behavior

	Price Scale	Share Searchers	Mean No. Searches if search	Median No. Searches if search	Gain Share if search
			Panel A: Student Subjects		
$S\,1.0$	[4.00, 8.00]	0.85	7.0 (6.6)	5	0.87
$S\,3.0$	[12.00, 24.00]	0.83	9.6 (15.1)	5	0.89
$S\,5.0$	[20.00, 40.00]	0.87	10.2 (12.1)	6	0.91
$S\,7.0$	[28.00, 56.00]	0.83	11.5 (17.2)	6	0.93
Observations		581	490	490	490
			Panel B: AMT Workers		
$S\,0.5$	[2.00, 4.00]	0.85	2.9 (4.1)	1	0.68
$S\,1.5$	[6.00, 12.00]	0.84	3.3 (9.0)	1	0.69
$S\,2.5$	[10.00, 20.00]	0.83	2.6 (3.3)	1	0.64
$S\,3.5$	[14.00, 28.00]	0.85	3.5 (6.8)	1	0.65
Observations		626	528	528	528

percent in $S\,0.5$ to 65 percent in $S\,3.5$, but the decrease 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 close to one for AMT workers. To confirm these results, we conducted two additional robustness checks (see Subsection 7.2). They yield roughly the same outcomes. Finally, only very few subjects take breaks between searches. Among students subjects, 25 searchers (5.1 percent) take at least one break of 2 or more minutes between searches. Among AMT workers, only 14 searchers (2.7 percent) take at least one such break.

5 Estimating Search Costs

We now turn to the estimation of search costs and the degree of diminishing sensitivity. 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. In Subsection 5.3, we show our estimation results. Finally, in Subsection 5.4, we examine the welfare consequences of diminishing sensitivity 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 $\gamma = 0$, 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 (6), we get that for $\gamma = 0$, her search costs equal

$$c(r, \gamma = 0) = \frac{(r-a)^2}{2(b-a)}. \tag{8}$$

If we could observe a subject's reservation price r, we could immediately back out her search costs from the above function $c(r, \gamma = 0)$. 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 $c(p_i^1, \gamma = 0) \le c_i \le c(p_i^2, \gamma = 0)$. If subject i searches exactly once, her search costs must be in the interval $c(p_i^1, \gamma = 0) \le c_i \le c(b, \gamma = 0)$. Finally, if subject i searches all 100 shops, her search costs must be in the interval $-\infty < c_i \le c(p_i^1, \gamma = 0)$.

We can now calculate for each treatment the the mean lower and mean upper bound on search costs. Table 3 shows the results. Among student subjects, the mean lower bound increases from 0.07 Euro in treatment $S1.0$ to 0.16 Euro in treatment $S7.0$. This increase is statistically significant (Jonckheere-Terpstra test, p-value < 0.001). Similarly, the mean upper bound on search costs increases from 0.59 Euro in treatment $S1.0$ to 2.85 Euro in treatment $S7.0$ (Jonckheere-Terpstra test, p-value < 0.001). For AMT workers, we find similar results. Their mean lower bound increases from 0.17 USD in treatment $S0.5$ to 1.47 USD in treatment $S3.5$, and their mean upper bound increases from 0.67 USD in treatment $S0.5$ to 5.00 USD in treatment $S3.5$ (Jonckheere-Terpstra test, p-value < 0.001 in both cases).

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 increasing relationship. Hence, one may instead interpret these findings as biased estimates in the standard search model ($\gamma = 0$) and as an indication for diminishing sensitivity in both subject pools. We explore this further in the next subsections where we estimate γ.

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: 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
		Panel B: 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

Notes: Standard errors are in parentheses.

5.2 Ordered Probit Model

To jointly estimate search costs and the degree of diminishing sensitivity in our experiment, we first derive search costs from reservation prices for any value of $\gamma \geq 0$. So we first generalize expression (8) obtained for $\gamma = 0$, under a uniform price distribution on $[a, b]$ and for reservation prices within this interval. From equation (6), we get that for $\gamma = 1$, her search costs would be equal to

$$c(r, \gamma = 1) = \frac{r - a + a(\ln a - \ln r)}{b - a}, \tag{9}$$

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

$$c(r, \gamma) = \frac{(1-\gamma)r^{2-\gamma} - (2-\gamma)ar^{1-\gamma} + a^{2-\gamma}}{(1-\gamma)(2-\gamma)(b-a)}. \tag{10}$$

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

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

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 7.3 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

$$\ln c_i = x_i\beta + \sigma\varepsilon_i, \tag{12}$$

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 (12) 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

$$\begin{aligned} P_i = \Pr(c(p_i^1,\gamma) \le c_i < c(p_i^2,\gamma)) &= \Pr(c(p_i^1,\gamma) \le \exp(x_i\beta + \sigma\varepsilon_i) < c(p_i^2,\gamma)) \\ &= \Phi\left(\frac{\ln c(p_i^2,\gamma) - x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma) - x_i\beta}{\sigma}\right). \end{aligned} \tag{13}$$

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

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

Similarly, for $n_i = 100$, we have

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

The log-likelihood function is given by

$$\ln L = \sum_{i=1}^{I} \ln P_i. \tag{16}$$

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

Standard Model. In this subsection, we describe the results from our ordered probit regressions. We start with the standard case without diminishing sensitivity, $\gamma = 0$. Table 4 shows the results. For both subject pools, the parameter $\tilde{\beta}_0$ indicates the average search costs. When diminishing sensitivity is ignored, student subjects incur on average search costs of 0.46 Euro per search and AMT workers even 2.30 USD per search. There is considerable unobserved heterogeneity in search costs. We estimate a standard deviation around the mean of 2.00 for student subjects and of 8.65 for AMT workers.

The estimated search costs differ substantially between treatments, see Columns 2 and 5 of Table 4. 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. Similary, for AMT workers, the average search costs per search are 0.42 USD in treatment $S0.5$ and 3.79 USD in treatment $S3.5$, an increase of around 795 percent. These differences are statistically significant in both cases (p-value < 0.006 and p-value < 0.001, respectively).

Note that the search cost estimates fall within the average lower and upper bounds of Table 3, and there is a similarly increasing pattern across treatments. Column 3 shows the ordered probit regression results when we add our standard controls: a dummy for above-median age, gender, and dummies for above-median willingness to take risk and CRT score. We obtain roughly the same results when we include these controls (the controls are not significant). Hence, under the standard random sequential search model without diminishing sensitivity, empirical search cost estimates increase in the price scale. This replicates the finding from empirical search cost studies that we highlighted in the introduction. Since the physical search costs are the same in all treatments, the estimation captures a misspecification bias. To take scale effects into account, we now allow for flexible degrees of diminishing sensitivity.

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 student subjects, we find a degree of diminishing sensitivity of $\gamma = 0.42$ and average search costs per search of 0.14 Euro. The diminishing sensitivity parameter is significantly different from zero (p-value < 0.001), but also significantly smaller than one, the value implied by the Weber-Fechtner law. For AMT workers, the ordered probit regressions yield us a degree of diminishing sensitivity of $\gamma = 0.98$ and average search costs per search of 0.17 USD. This degree of diminishing sensitivity is again different from zero (p-value < 0.001) and very close to, and insignificantly different from, the value suggested by the Weber-Fechtner law.

Table 4: Search Costs Estimates without Diminishing Sensitivity ($\gamma = 0$)

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

Notes: Separate search costs per treatment, based on ordered probit (16) 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; $\tilde{\beta}_0 = \exp(\beta_0 + \frac{\sigma^2}{2})$; $\tilde{\beta}_j = \exp(\beta_j + \frac{\sigma^2}{2})$ 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 *** $p < 0.01$.

We can now 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 student subjects and in Column 3 for AMT workers, 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 $\gamma = 0$ (i.e., Columns 2 and 5 from Table 4) to facilitate the comparison. For student subjects, the average search costs per search vary between 0.12 Euro and 0.16 Euro. As expected, the differences are never significant (p-value > 0.367). For AMT workers, the average search costs per search vary between 0.14 USD and 0.19 USD. Again, these differences are not significant (p-value > 0.100). Furthermore, 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: 77 percent in $S7.0$ for student subjects, and 95 percent in $S3.5$ for AMT workers. Also note that the estimated search costs are quite similar

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

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

Notes: Single search cost parameter across treatments, based on ordered probit (16) with flexible γ; $\tilde{\beta}_0$ 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 students and AMT workers.[11] In contrast, when we assume $\gamma = 0$, 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 subjects who are more willing to take risks have higher search costs, and that subjects with a higher CRT score tend to have lower search costs. Nevertheless, the control variables do not seem to explain much of the heterogeneity in search costs, as can be seen from our estimate of the standard deviation which remains essentially unchanged. 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

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

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

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

Notes: Separate search costs per treatment, based on ordered probit (16) 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; $\tilde{\beta}_j = \exp(\beta_j + \frac{\sigma^2}{2})$ 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 *** $p < 0.01$.

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 for student subjects and AMT workers. There is substantial heterogeneity in both subject pools. For student subjects, the distribution has a single peak around very small search costs. For AMT workers, the distribution exhibits two peaks, one around very small search costs and one around 0.08 USD.

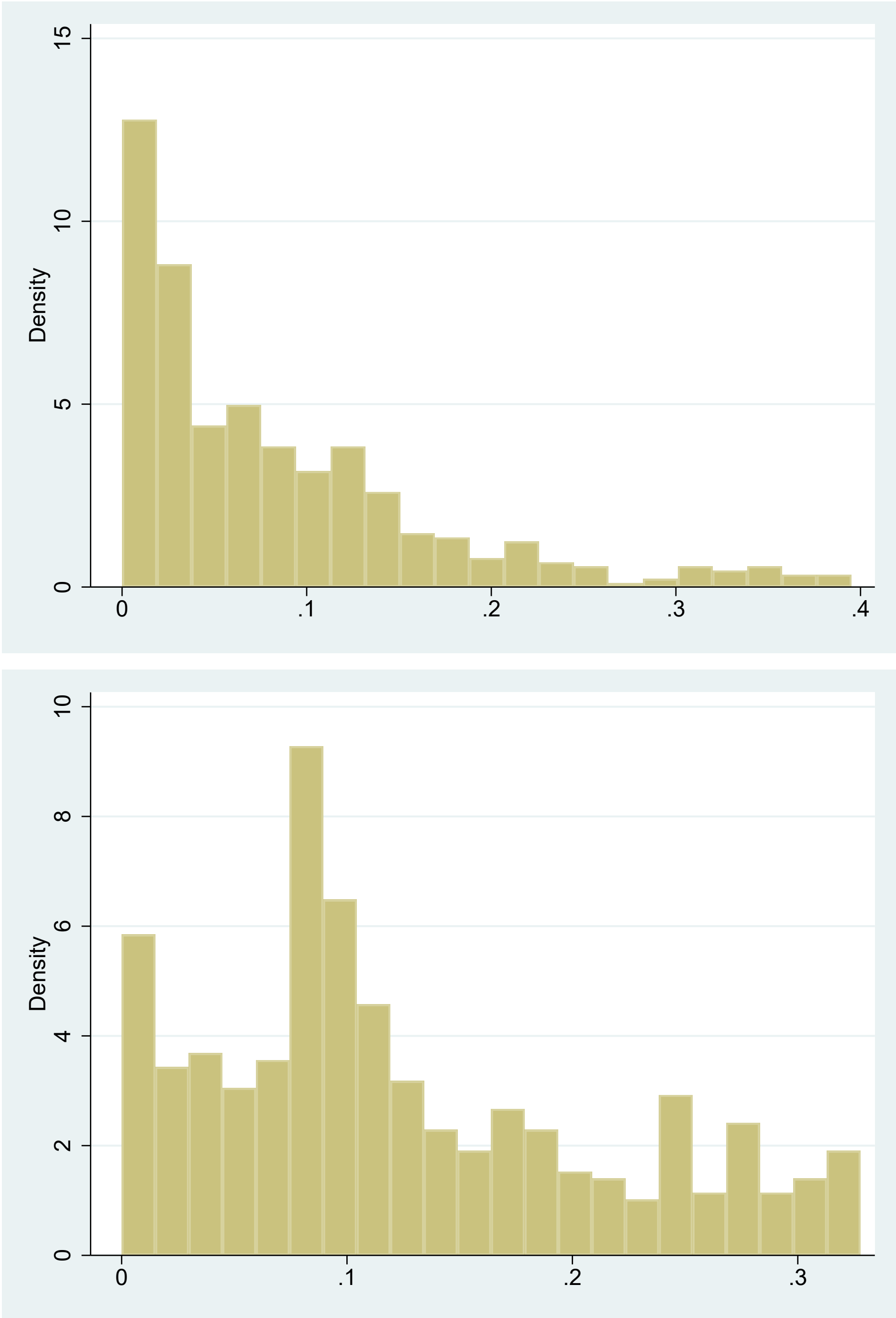

Figure 1: Distribution of expected individual search costs per search for student subjects (upper graph) and AMT workers (lower graph), for flexible degrees of diminishing sensitivity.

5.4 Welfare

Using our utility framework, we can assess the welfare consequences of diminishing sensitivity 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 diminishing sensitivity and the experienced utility when decision-making is subject to diminishing sensitivity. We first derive the absolute welfare loss of a decision-maker who exhibits diminishing sensitivity of degree γ. 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 (6). The decision-maker's (expected) experienced utility from search is given by

$$u - \mathbb{E}[p \mid p \leq r_\gamma] - \frac{c}{F(r_\gamma)}. \tag{17}$$

The absolute welfare loss from diminishing sensitivity then equals the difference in the payoffs from equations (3) and (17):

$$\text{absolute welfare loss} = \Big(\mathbb{E}[p \mid p \leq r_\gamma] - \mathbb{E}[p \mid p \leq r]\Big) + \left(\frac{1}{F(r_\gamma)} - \frac{1}{F(r)}\right)c. \tag{18}$$

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 (18) becomes

$$\frac{1}{2}(r_\gamma - r) - \frac{(r_\gamma - r)(b - a)}{(r_\gamma - a)(r - a)}c. \tag{19}$$

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

$$b - \mathbb{E}[p \mid p \leq r] - \frac{c}{F(r)}. \tag{20}$$

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

$$(b - a) - \sqrt{2(b - a)c}. \tag{21}$$

The ratio between the absolute welfare loss in equation (19) and the absolute utility gains from search in equation (21) constitute her relative welfare loss.

Table 7: Relative Welfare Loss – Comparative Statics

	$\gamma = 0.4$			$\gamma = 0.7$			$\gamma = 1.0$		
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

We compile the relative welfare loss in our setting for varying search costs, degrees of diminishing sensitivity, and price scales. 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 student subjects and AMT workers; see the distribution over expected search costs in Figure 1. For degrees of diminishing sensitivity, we select the values $\gamma \in \{0.40, 0.70, 1.00\}$ so that we have, roughly, the student subjects' and the AMT workers' degree of diminishing sensitivity, as well as an intermediate level. For price scales, we take the original scales from our experiment (top panel), and also consider much higher scales as search markets for expensive products (lower panel).

Table 7 shows the results. For $\gamma = 0.40$, the relative welfare loss due to diminishing sensitivity is fairly modest, even for subjects with substantial search costs, or for very high price scales. Typically, it is less than 4 percent of the absolute welfare. This also holds for higher prices. In contrast, for $\gamma = 1.00$ we find substantial welfare losses among all search cost levels. At higher 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. Note finally that the relative welfare loss may not increase monotonically with the price scale, in particular at lower values of γ. At a sufficiently large scale, the relative welfare loss drops. In summary, the welfare loss due to diminishing sensitivity can be quite substantial.

6 Search Time and Average Hourly Earnings

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

We first provide an overview of two key search duration variables. 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. The "mean total duration" is the time (in seconds) between entering the overview page and buying the product. Table A9 in the Appendix shows the mean and the median of these variables in all treatments. The mean search duration is roughly 60 seconds for student subjects and 85 seconds for AMT workers. There are no significant differences between treatments (one-way ANOVA, p-value = 0.626 for students, and p-value = 0.700 for AMT workers). For student subjects, the results for total duration largely mirror those for the number of searches. They spend significantly more time on search in higher scale treatments (Jonckheere-Terpstra test, p-value < 0.001), but the increase in search time is modest and is partly driven by a few subjects who search extensively in high scale treatments. For AMT workers, there are no significant differences in the mean total duration between treatments (one-way ANOVA, p-value = 0.788).

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

$$\text{direct search costs} = \text{average hourly earnings} \times \frac{\text{mean search duration}}{3600}. \tag{22}$$

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

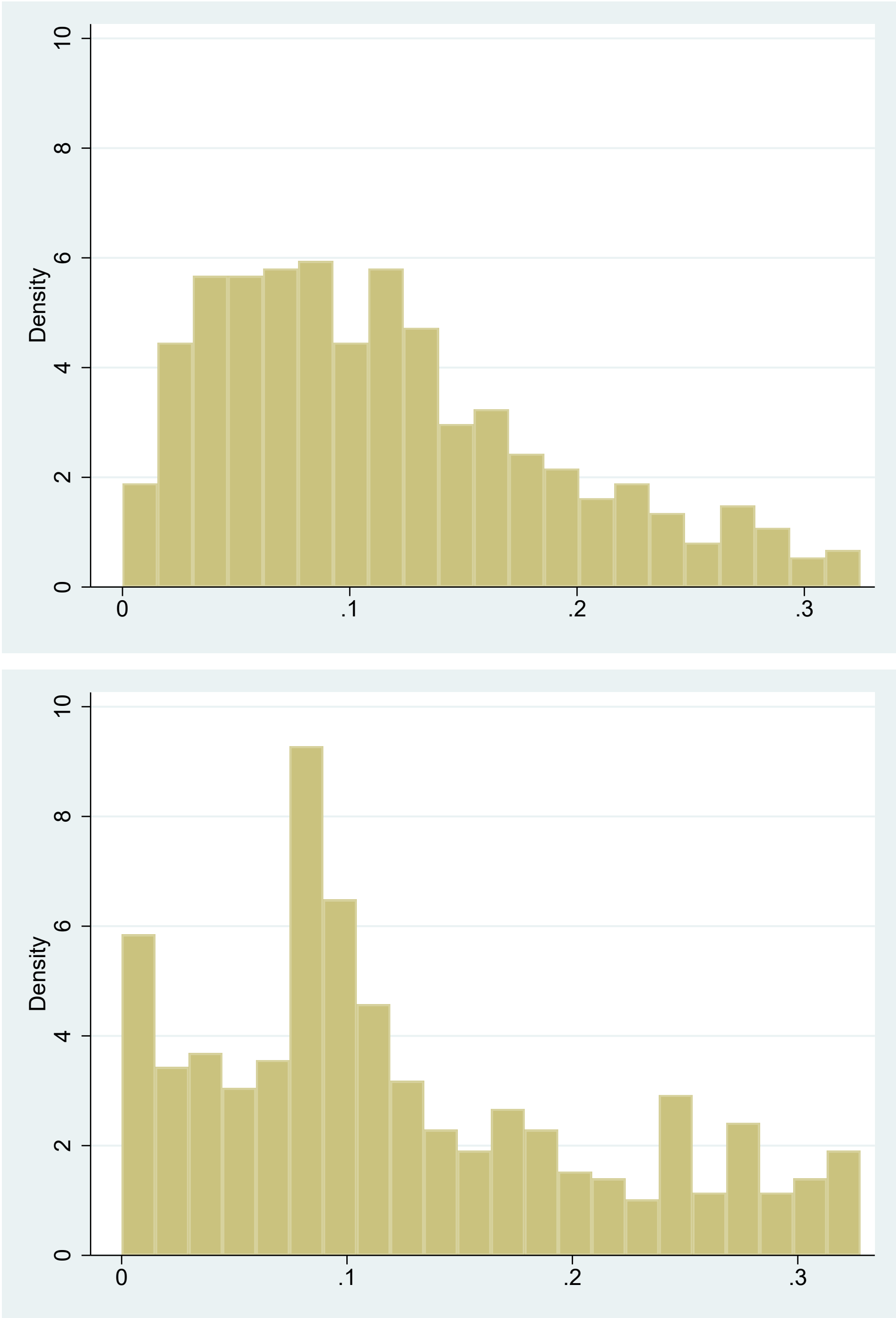

Figure 2: Direct search costs (upper graph) and expected individual search costs for flexible degrees of diminishing sensitivity (lower graph) of AMT workers.

Next, we examine the relationship between the two search cost measures. There should be a positive relationship between the model's predicted and direct search costs. Table A10 in the Appendix shows the results from a linear regression of the log of predicted search costs on the log of direct search costs. We indeed find a positive relationship between the search cost measures. For a one percent increase in direct search costs there is a 0.24 percent (0.23 percent) increase in predicted search costs according to the model without (with) our standard controls. There is, however, a lot of unexplained heterogeneity as can be seen from the low R^2 values.[12]

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

7 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 7.1, we examine our estimates when we change the composition of treatments. In Subsection 7.2, 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 7.3, we relax the assumption that search costs are log-normally distributed. In Subsection 7.4, we explain why increasing search costs are unlikely to explain our results. Finally, in Subsection 7.5, we consider an alternative approach – relative thinking as defined by Bushong et al. (2021) – that can be used to obtain scale-independent search cost estimates.

7.1 Composition of Treatments

We used the data from all four scale treatments to jointly estimate search costs and the degree of diminishing sensitivity. One also could run the experiment with other scale variations. It

[12]Instead of this linear regression, we also considered an alternative approach where we include the log of direct search costs as a covariate in x_i our ordered probit model. This gave very similar conclusions.

is therefore unclear to what extent our results depend on the composition of treatments. To examine whether our results are robust to variations in the treatment composition, we run our ordered probit regressions with only two instead of four scale treatments. It turns out that we obtain very similar estimation results as long as the two scales are sufficiently different from each other. We obtain the following results:

treatments used for estimation	Estimated Dim. Sensitivity	Estimated Search Costs
Panel A: Student Subjects		
all	$\gamma = 0.42$	$c = 0.14$
$S\,1.0$ and $S\,7.0$	$\gamma = 0.42$	$c = 0.12$
$S\,1.0$ and $S\,5.0$	$\gamma = 0.48$	$c = 0.11$
Panel B: AMT Workers		
all	$\gamma = 0.98$	$c = 0.17$
$S\,0.5$ and $S\,3.5$	$\gamma = 1.02$	$c = 0.16$
$S\,0.5$ and $S\,2.5$	$\gamma = 1.01$	$c = 0.17$

Therefore, we need only two treatments to estimate search costs and the degree of diminishing sensitivity in our search experiment. However, when we use scale treatments that are closer to each other than those used above, estimation results become more diverse. Thus, identifying the sensitivity parameter requires sufficient variation in price scales.

7.2 Search on Amazon Mechanical Turk

The AMT workers in our sample spend relatively little effort on search, despite substantial incentives. One may suspect that a lack of understanding or attention partially drives this result. 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 degree of diminishing sensitivity. The estimation results are as follows:

AMT sample used for estimation	$S0.5$ Mean No. Searches	$S3.5$ Mean No. Searches	Estimated Dim. Sensitivity	Estimated Search Costs
all subjects	2.9 (4.1)	3.5 (6.8)	$\gamma = 0.98$	$c = 0.17$
university degree only	2.7 (4.5)	2.9 (4.2)	$\gamma = 1.02$	$c = 0.15$
high CRT score	3.3 (4.9)	4.1 (7.7)	$\gamma = 1.03$	$c = 0.12$
Part 1 above median time	2.9 (5.0)	4.2 (9.1)	$\gamma = 0.91$	$c = 0.24$

In the considered subsamples, the amount of search as well as the estimated parameter values for search costs and the degree of diminishing sensitivity slightly vary around those of the full sample. Only for the AMT workers who spent more time on Part 1 than the median worker we observe a smaller degree of diminishing sensitivity. 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 estimates for the AMT workers.

To further evaluate search on AMT, we conduct two robustness checks with a new sample of 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 A12 and Table A13 in the appendix contain the demographic information as well as the most important results on average search behavior, estimated search costs (for $\gamma = 0$ as well as flexible γ), search time, and direct 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 diminishing sensitivity into account, estimated search costs increase by a factor of five from $S0.5$ to $S3.5$. With diminishing sensitivity, we obtain the following results.

	$S0.5$ Mean No. Searches	$S3.5$ Mean No. Searches	Estimated Dim. Sensitivity	Estimated Search Costs
Robustness Check 1	1.9 (1.9)	3.3 (5.2)	$\gamma = 0.79$	$c = 0.25$
Robustness Check 2	2.3 (2.7)	3.1 (4.6)	$\gamma = 0.76$	$c = 0.27$

Thus, the estimated degrees of diminishing sensitivity are slightly smaller and the estimated search costs slightly larger than in the baseline study (and 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 degree of diminishing sensitivity. That being said, it needs to be mentioned that in a typical online search environment the benefits from search are not very salient.

7.3 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

$$g(c) = \frac{c^{\lambda} - 1}{\lambda} \text{ if } \lambda \neq 0 \text{ and } g(c) = \ln c \text{ if } \lambda = 0. \tag{23}$$

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 γ and λ using maximum likelihood estimation. Moreover, we estimate γ for fixed values $\lambda = 0$ (log-normally distributed search costs) and $\lambda = 1$ (normally distributed search costs).

Table A11 in the appendix shows the results. For student subjects, the estimated degree of diminishing sensitivity γ varies between 0.42 and 0.69. The estimated Box-Cox parameter λ equals 0.16. Hence, for student subjects the distribution of search costs is close to the log-normal distribution; the corresponding γ equals 0.51. For AMT workers, the estimated degree of diminishing sensitivity γ lies between 0.98 and 1.07; the estimated Box-Cox parameter λ is 0.50 and the corresponding γ is 1.05. We conclude that our main results regarding diminishing sensitivity continue to hold under a distributional assumption on search costs that is more flexible than the assumption of log-normality.

7.4 Increasing Search Costs

The classic sequential search model assumes that search costs per search are constant in the number of searches. Most empirical search models stick to this assumption. However, in general, it may also be possible that search costs increase or decrease in the number of searches, depending on the setting. In our case, increasing search costs could, in principle, explain student subjects' search behavior and the increase in the search cost estimates without taking diminishing sensitivity into account (for AMT workers, the number of searches is roughly the same in all treatments, so increasing search costs cannot rationalize our findings for these subjects). Nevertheless, we argue in the following that this is quite implausible.

Search in our setting is akin to a simple data entry job that does not require cognitive effort and for which it is common to hire students as research assistants (at a wage of around 13.50 Euro per hour in Innsbruck). A back-of-the-envelope calculation shows that if increasing search costs would explain our findings, this would imply unreasonable high hourly reservation wages for our student subjects. From Table 4 and from Table A9 we get that, in treatment $S\,1.0$, 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 $S\,7.0$, 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 34.74 Euro in treatment $S\,7.0$. 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[13], which implies an 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.

A further reason why increasing search costs are unlikely to explain our results is that 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. As discussed in Subjection 4.2, few subjects have a break between searches. Therefore, we believe that increasing search costs cannot explain our findings.

7.5 Relative Thinking and Search Cost Estimates

To obtain scale-independent search cost estimates, we allowed for diminishing sensitivity with respect to prices in the decision-maker's indirect utility function. Diminishing sensitivity is a behavioral pattern that is assumed in several choice theories. There exist, however, alternative behavioral mechanisms that can rationalize scale-dependent search costs. In a recent paper, Bushong et al. (2021), henceforth BRS, formalize a utility theory of "range-based relative thinking." In this model, the decision-maker's utility weight on the outcome of a given consumption dimension (such as money or leisure) depends on the variability of the outcomes in this dimension. This variability is defined by the choice set. The larger the variability of

[13]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.

outcomes in a certain dimension, the smaller is the weight on outcomes in this dimension in the decision-maker's utility function. Saving a given amount by exerting effort then appears as less desirable if the range of possible payments is large than if it is small. In the context of price search, relative thinking thus has similar implications as diminishing sensitivity.

The BRS model of relative thinking can be adapted to our sequential search setup. According to this model, the decision utility from purchasing the good at price p and spending L on search is given by the indirect utility function

$$V^{rt}(p, L) = u - w_1(\Delta)p - w_2 L, \tag{24}$$

where the function $w_1(.)$ is the decision weight in the money dimension, Δ is the range of outcomes in the money dimension, and the scalar w_2 is the weight in the leisure dimension; since there is no variation in this dimension in our setting, we normalize $w_2 = 1$. Given the price interval $[a, b]$, the range of outcomes in the money dimension Δ equals the difference between the highest and lowest price, $\Delta = b - a$.

BRS assume that the weighting function $w_1(.)$ is a strictly decreasing function in Δ. In order to jointly estimate search costs and the degree of relative thinking, we use the parameterized version of $w_1(.)$ from Somerville (2022). With this parametrization, we obtain scale-independent search cost estimates, see Appendix A.6 for details. These estimates are actually fairly close to those in Section 5. Thus, there are several behavioral theories that lead to similar conclusions and that can rationalize the positive relationship between (classic) search cost estimates and the value of the transaction.

8 Conclusion

Search costs measure how easy it is for consumers to compare prices and to find the best product for their needs. Digital markets have the potential to make consumer search convenient and therefore to exert competitive pressure on firms. However, empirical search cost estimates for digital markets are typically large, which is often difficult to reconcile with 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 for a modest wage?

We proposed that there is a positive relationship between cost estimates and price scales. To verify this claim, we conducted an online search experiment in which we can vary the price scale of a hypothetical product without changing the effort required to obtain a price quote. 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 search cost estimates increase considerably in the price scale when estimated in a standard fashion. In the highest price scale treatments, these estimates are unreasonably large relative to the time needed to obtain a price quote.

To explain large search cost estimates that increase in the price scale, we proposed that individuals exhibit diminishing sensitivity (or relative thinking): They tend to become less sensitive to fixed price variations when the price scale of the good increases. Therefore, they may undervalue the gains from search, in particular, when prices are high. We modified the random sequential search model so that it allows for diminishing sensitivity, and estimated both search costs and the degree of diminishing sensitivity with our experimental data. Allowing for diminishing sensitivity roughly equalizes the search cost estimates in the different scale treatments. On average, student subjects require around 0.14 Euro for a 60 seconds investment into getting a price quote. Online workers at Amazon Mechanical Turk request a payment of 0.17 USD for the 85 seconds they need to find another price. On the aggregate level, this estimate is roughly consistent with the AMT workers' opportunity costs of time, which we infer from their average hourly earnings and the time they need to find a price.

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 diminishing sensitivity. 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.

Future empirical research on search costs can address this issue 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 the AMT workers). 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 diminishing sensitivity 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 searchers' degree of diminishing sensitivity 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 degree of diminishing sensitivity. However, an alternative to price scale variations may be to study search for multiple items with differing price scales. Individual data on search for multiple items may even allow researchers to test whether there exist significant differences in the degree of diminishing sensitivity within the population.

Our approach leaves open several other questions that researchers can address in future experimental and empirical work. We showed that both models with 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. It may be possible to disentangle different mechanisms with an updated experimental design. Moreover, 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.

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A Appendix

A.1 Proof of Proposition 1

We define $rz = r_\gamma(z)$ so that we can write the indifference condition as

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

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 strictly negative for $\gamma < 1$ and equal to zero for $\gamma = 1$. From this the first two statements follow 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 third statement.

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.

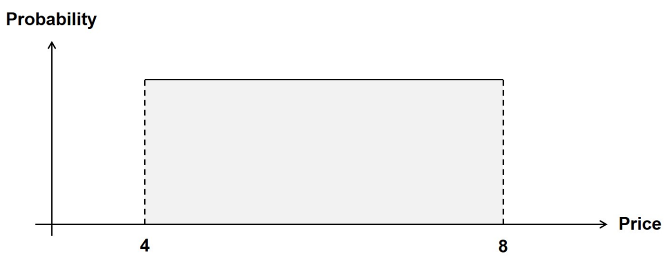
You can simply buy product A for 8 USD. **You do not need to do anything else for this. All the earnings will be paid automatically.**

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.[14]

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 59.4 percent of student subjects and 87.7 percent of AMT workers indeed purchase from the last sampled shop or search all 100 shops (six student subjects did 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 student subjects (one-sided t-tests, p-values < 0.001) and AMT workers (one-sided t-tests, p-values < 0.014). 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 EUR/USD. These results originate from a linear probability regression model, see Column 3 and Column 4 of Table A3 and Table

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

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

Table A2: Search and Recall

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

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

Table A3: 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 *** $p < 0.01$.

Table A4: 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 *** $p < 0.01$.

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

$$\phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right) \text{ and } \Phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right), \tag{28}$$

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

$$\phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right)\frac{1}{c_i} \text{ and } \Phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right). \tag{29}$$

The (unconditional) expected value of search costs equals

$$\mathbb{E}[c_i] = \exp\left(x_i\beta + \frac{\sigma^2}{2}\right). \tag{30}$$

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

$$\mathbb{E}[c_i \mid c(p_i^1, \gamma) \leq c_i < c(p_i^2, \gamma)] = \int_{c(p_i^1,\gamma)}^{c(p_i^2,\gamma)} \frac{c_i\phi\left(\frac{\ln c_i - x_i\beta}{\sigma}\right)\frac{1}{c_i}}{\Phi\left(\frac{\ln c(p_i^2,\gamma)-x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma)-x_i\beta}{\sigma}\right)} dc_i. \tag{31}$$

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

$$\mathbb{E}[c_i \mid c(p_i^1, \gamma) \leq c_i < c(p_i^2, \gamma)] = \mathbb{E}[c_i] \cdot \frac{\Phi\left(\frac{\ln c(p_i^2,\gamma)-(x_i\beta+\sigma^2)}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma)-(x_i\beta+\sigma^2)}{\sigma}\right)}{\Phi\left(\frac{\ln c(p_i^2,\gamma)-x_i\beta}{\sigma}\right) - \Phi\left(\frac{\ln c(p_i^1,\gamma)-x_i\beta}{\sigma}\right)}. \tag{32}$$

A.5 Robustness Checks

In the first robustness check, we updated the information that we 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. Finally, we show the precise wording of the comprehension question in the second robustness check.

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 1

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 2

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 Relative Thinking and Search Cost Estimates

We first adapt the BRS model to the random sequential search setting and then we present our search cost estimates. Since for a given range Δ the weighting function only scales prices, the optimal search strategy at constant search costs c remains a reservation price policy. From the decision utility in equation (24) we get that the reservation price is implicitly defined by the indifference condition

$$c = \int_a^r w_1(\Delta)\,(r-p)\,f(p)dp. \tag{33}$$

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

$$c(r) = \frac{w_1(\Delta)(r-a)^2}{2(b-a)}. \tag{34}$$

BRS assume that the weighting function $w_1(.)$ is a differentiable, decreasing function on $(0, \infty)$, and that $w_1(\Delta) \times \Delta$ is strictly increasing. This leaves open various possible functional forms. In a recent paper, Somerville (2022) uses the following functional form, which is also suitable for our setting:[15]

$$w_1(\Delta) = \frac{1}{\Delta^\rho}, \tag{35}$$

with $\rho \in \mathbb{R}$. For convenience, we call ρ the "degree of relative thinking." If $\rho = 0$, we obtain the standard search model. If $\rho = 1$, we obtain scale-independent search behavior.

Next, we jointly estimate search costs and the degree of relative thinking ρ using our ordered probit regression framework from Subsection 5.2. We only have to replace the search cost equation (10) by the new equation (34), and we assume that the weighting function is given by equation (35). Columns 1 and 3 of Table A5 show the results from our ordered probit regressions with flexible ρ.

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 $\rho = 0.34$. 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.[16] The search cost estimates for the two subject pools therefore are rather close to those from the model with diminishing sensitivity.

[15] Somerville (2022) conducts experiments in which he tests BRS 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.

[16] Note that a ρ above one is possible in our framework as long as $w_1(\Delta) > 0$. This condition is always satisfied.

Table A5: Search Costs and ρ Estimates

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

Notes: Ordered probit regressions 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 *** $p < 0.01$.

In Columns 2 and 4 of Table A5, 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. Taken together, these results are quite in line with those for the diminishing sensitivity model.

We compare the estimated average search costs between treatments for given (estimated) values of ρ (analogous to the exercise for the model with diminishing sensitivity in Table 6). Table A6 shows the results in Column 1 for student subjects and in Column 3 for AMT workers. In Columns 2 and 4, we again display the regression results from the standard model ($\rho = 0$). For student subjects, the average search costs per search vary between 0.13 Euro and 0.15 Euro. The differences are never significant (p-values > 0.434). For AMT workers, the average search costs per search vary between 0.19 USD and 0.21 USD. Again, these differences are never significant (p-values > 0.602).

Table A6: Search Costs Estimates, fixed ρ

	(1)	(2)	(3)	(4)
	Panel A: Student Subjects		*Panel B: AMT Workers*	
$S\,1.0/S\,0.5$	0.131***	0.247***	0.192***	0.424***
	(0.027)	(0.050)	(0.031)	(0.069)
$S\,3.0/S\,1.5$	0.154***	0.481***	0.198***	1.528***
	(0.032)	(0.101)	(0.031)	(0.237)
$S\,5.0/S\,2.5$	0.140***	0.551***	0.207***	2.860***
	(0.029)	(0.113)	(0.032)	(0.444)
$S\,7.0/S\,3.5$	0.126***	0.579***	0.187***	3.794***
	(0.027)	(0.124)	(0.027)	(0.558)
$\tilde{\sigma}$	0.569***	1.826***	0.512***	4.486***
	(0.139)	(0.447)	(0.084)	(0.739)
ρ	0.457	0.000	1.141	0.000
Controls	No	No	No	No
Observations	490	490	528	528

Notes: Ordered probit regressions with ρ fixed at the estimated values from Table A5 and at zero. 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 *** $p < 0.01$.

A.7 Additional Tables

Table A7: Descriptive Statistics Across Treatments, all subjects

Treatment	$S\,1.0/S\,0.5$	$S\,3.0/S\,1.5$	$S\,5.0/S\,2.5$	$S\,7.0/S\,3.5$	One-way ANOVA p-value
			Panel A: Student Subjects		
Age	23.3 (3.0)	23.7 (3.2)	23.4 (3.0)	23.5 (3.6)	0.716
Gender (share females)	0.65	0.59	0.64	0.60	0.626
Willingness to take risk	5.5 (2.3)	5.7 (2.1)	5.4 (2.1)	5.2 (2.2)	0.209
CRT score	2.0 (1.1)	2.1 (1.1)	2.1 (1.1)	2.1 (1.1)	0.997
Economics	0.30	0.29	0.24	0.33	0.398
Observations	148	146	143	144	
			Panel B: AMT Workers		
Age	40.5 (11.7)	39.4 (11.2)	40.2 (12.8)	38.7 (11.2)	0.522
Gender (share females)	0.48	0.44	0.44	0.40	0.597
Willingness to take risk	5.8 (2.8)	5.8 (2.7)	6.1 (2.7)	5.8 (2.7)	0.747
CRT score	1.7 (1.2)	1.8 (1.2)	1.5 (1.3)	1.7 (1.2)	0.148
Education	2.9 (0.8)	2.9 (0.7)	3.0 (0.7)	2.9 (0.7)	0.350
Average hourly earnings	7.0 (8.2)	7.5 (7.7)	8.3 (9.4)	6.4 (4.3)	0.147
Average hours per week	20.9 (15.0)	22.0 (14.3)	19.5 (14.5)	20.7 (16.1)	0.545
Observations	140	161	153	172	

Notes: Age is in years, willingness to take risk is on a scale from 0 (not willing to take risk at all) to 10 (very willing to take risk), CRT score is on a scale from 0 to 3, education is on a scale from 0 to 4 (0 = No degree, 1 = Some high school, 2 = High school degree, 3 = Bachelor's degree, 4 = Master's degree or higher), average hourly earnings is in USD.

Table A8: Descriptive Statistics Across Treatments, searchers only

Treatment	$S1.0/S0.5$	$S3.0/S1.5$	$S5.0/S2.5$	$S7.0/S3.5$	One-way ANOVA p-value
			Panel A: Student Subjects		
Age	23.4 (3.1)	23.5 (2.9)	23.5 (3.2)	23.2 (2.9)	0.887
Gender (share females)	0.63	0.60	0.65	0.56	0.536
Willingness to take risk	5.5 (2.2)	5.7 (2.0)	5.3 (2.1)	5.2 (2.2)	0.380
CRT score	2.1 (1.1)	2.0 (1.1)	2.1 (1.0)	2.1 (1.1)	0.966
Economics	0.32	0.30	0.25	0.34	0.495
Observations	126	121	124	119	
			Panel B: AMT Workers		
Age	41.3 (11.9)	40.0 (11.3)	40.3 (12.7)	38.6 (10.7)	0.296
Gender (share females)	0.50	0.41	0.46	0.41	0.365
Willingness to take risk	5.6 (2.9)	5.5 (2.6)	6.0 (2.6)	5.7 (2.6)	0.500
CRT score	1.8 (1.2)	1.9 (1.2)	1.6 (1.3)	1.8 (1.2)	0.119
Education	2.9 (0.8)	2.9 (0.7)	3.0 (0.8)	2.9 (0.7)	0.546
Average hourly earnings	7.1 (7.9)	7.1 (5.5)	8.2 (8.7)	6.3 (4.2)	0.138
Average hours per week	20.6 (14.4)	20.8 (12.8)	18.8 (13.5)	20.1 (15.3)	0.655
Observations	119	135	127	147	

Notes: Age is in years, willingness to take risk is on a scale from 0 (not willing to take risk at all) to 10 (very willing to take risk), CRT score is on a scale from 0 to 3, education is on a scale from 0 to 4 (0 = No degree, 1 = Some high school, 2 = High school degree, 3 = Bachelor's degree, 4 = Master's degree or higher), average hourly earnings is in USD.

Table A9: Descriptive Statistics – Search Time

	Price Scale	Mean Search Duration	Median Search Duration	Mean Total Duration	Median Total Duration
		Panel A: Student Subjects			
$S1.0$	[4.00, 8.00]	62 (32)	55	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
Observations		487	490	469	490
		Panel B: AMT Workers			
$S0.5$	[2.00, 4.00]	89 (70)	64	274 (356)	177
$S1.5$	[6.00, 12.00]	84 (64)	68	249 (330)	150
$S2.5$	[10.00, 20.00]	86 (54)	73	281 (399)	161
$S3.5$	[14.00, 28.00]	81 (58)	66	299 (494)	167
Observations		516	528	503	528

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

Table A10: 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 A11: γ Estimates under (log) normal distribution and Box-Cox transformation

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

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 A12: Results from Robustness Checks

	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 Cost Estimates, $\gamma = 0$	(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

Notes: Search Cost Estimates, $\gamma = 0$: Same regressions as in Table 4 (without controls). Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A13: Results from Robustness Checks (continuation)

	Panel A: Robustness 1		*Panel B: Robustness 2*	
Search Cost Estimates, flexible γ	(1)		(2)	
$\tilde{\beta}_0$	0.249***		0.272***	
	(0.052)		(0.071)	
$\tilde{\sigma}$	0.404***		0.631***	
	(0.108)		(0.215)	
γ	0.793***		0.757***	
	(0.088)		(0.103)	
Observations	232		246	
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)	
$R1/R2$	0.329 (0.629)		0.170 (0.300)	
Search Cost Estimates, flexible ρ	(1)		(2)	
$\tilde{\beta}_0$	0.338***		0.329***	
	(0.063)		(0.076)	
$\tilde{\sigma}$	0.640***		0.876***	
	(0.157)		(0.267)	
ρ	0.835***		0.847***	
	(0.094)		(0.106)	
Observations	232		246	

Notes: Notes: Search Cost Estimates, flexible γ: Same regressions as in Table 5 (without controls). Search Cost Estimates, flexible ρ: Same regressions as in Table A5 (without controls). Significance at * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.