Preventing Search with Wicked Defaults*

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Abstract

We study theoretically and experimentally a setting where a buyer chooses one of several available options whose values are initially unknown but can be discovered through costly search. In the baseline condition, the starting point of search is random. In a wicked-default condition, the starting point of search is set optimally by a profit-maximizing seller. Low-cost buyers are better off, while high-cost buyers are worse off. Our experimental results are consistent with these predictions, even though the effect sizes are moderated due to sub-optimal search. Sellers benefit from wicked defaults even when their motivations are revealed.

Keywords: wicked defaults, costly search, theory, experiment
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1 Introduction

Defaults have emerged as an important policy tool for nudging individuals into socially beneficial choices (Sanders, Snijders and Hallsworth, 2018; DellaVigna and Linos, 2022). In the hands of benevolent "choice architects," defaults (i) do not restrict the choices of consumers who are informed and active in their decision making process, but (ii) help improve the choices made by individuals who are challenged making decisions and who make bad (or no) decisions as a result. As such, defaults are seen as light-touch "Libertarian Paternalistic" policies that can improve the outcomes for confused or uninformed individuals while respecting the freedom of others (Thaler and Sunstein, 2003; Sunstein, 2014; Jachimowicz et al., 2019).

Despite being celebrated as an important policy tool, there is the risk that defaults can be exploitative when interests are misaligned. We call defaults designed to benefit the choice architect rather than the target of the choice architecture *wicked* because they are opportunistic in nature and exploit, rather than help, passive consumers.

We study wicked defaults theoretically and experimentally in the context of a profit-maximizing firm that can use defaults to strategically influence the information acquired by its consumers. Dating back to Simon (1955), it has been posited that many individuals make choices using an item-by-item sequential search process that includes a stopping rule when individuals identify a choice with a sufficiently high level of utility. Such "satisficing" behavior appears to be a common approach to complex decision making (Conlisk, 2003; Bhatia et al., 2021), and has been documented experimentally (e.g., Caplin, Dean and Martin, 2011). Our interest is in understanding how defaults might be used to exploit individuals who exhibit satisficing behavior and to explore behaviorally how individuals respond to defaults that might be wicked.

We show, theoretically and experimentally, how defaults can be used to prevent information acquisition and to exploit consumers when search is costly. Our search model is in the tradition of McCall (1970) and Weitzman (1979) where individuals must search sequentially over a finite set of products to learn their underlying value. When consumers know about the distribution of values and evaluating each new product is costly, optimal search requires a threshold stopping rule so that search continues until a threshold utility is achieved or all objects are evaluated.

We show that the firm can strategically offer defaults that fall within a consumer's acceptance set. These offers prevent additional search and guide consumers to products that are optimal for the firm to sell. The consumer receives products that are worse on average than what they would have received if they searched on their own in a random order, but economize on search costs. On net, the firm will always be made better off by setting a default because it is able to extract the expected rents associated with search. The consumer may be worse off under a wicked default if there is a strong misalignment in the ordering of products between the consumer and the firm and if the consumer's costs of search are sufficiently high.

Our model provides a rational mechanism by which self-interested firms can exploit defaults. Further, the range of economic decision making problems for which such defaults might be used is quite general and includes any problem for which information acquisition is costly and decision making involves a threshold stopping rule. The channel is also distinct from many of the rationales for defaults offered in the literature, which commonly have behavioral underpinnings such as a status-quo bias or quasi-hyperbolic discounting (e.g., Choi et al., 2003, 2004; Carroll et al., 2009; Dinner et al., 2011).

Although our theoretical results are compelling, the experimental literature on search (discussed below) has found that individuals adopt a wide variety of strategies when faced with sequential search and are not always optimal in their search decisions (Bhatia et al., 2021). As such, it is important to understand whether there are behavioral responses to defaults that are not captured by our theoretical model. We hence provide experimental evidence that defaults do indeed influence the behavior of individuals faced with sequential search problems and that the main comparative statics of the model hold.

Subjects in our experiment faced a total of 80 sequential search problems. In each problem, an individual faces a sequence of 10 options with values drawn from a known distribution. The first option—the default—is always revealed, and the rest are initially hidden. Individuals can either accept the default option or reveal one of the hidden options at a cost. They can keep searching or stop at any point and accept the best revealed offer so far. In half of the periods (assigned in a random order), the entire search sequence, including the default, is random, while in the other half we modify the search order by initially offering individuals a wicked-default option, i.e., the lowest valued option in the theoretical acceptance set. In addition to this within-subject variation in default setting, we conduct between-subject treatments varying participants' search costs.

We find, in agreement with theory, stark negative effects of wicked defaults on buyers' welfare when search costs are high; and small, but statistically significant, positive effects when search costs are low. This is despite our buyers mostly searching excessively and earning below the theoretical predictions. As a consequence of these deviations from optimal search behavior, the firm does not benefit from wicked defaults when dealing with low-cost buyers. The firm does, however, benefit from offering wicked defaults to high-cost buyers, albeit to a lesser extent than theoretically predicted.

Our framework also allows us to explore the interaction between defaults and trust. While we study wicked defaults theoretically and experimentally in the context of a profit-maximizing firm that can use defaults to strategically influence the information acquired by its consumers, we do not tell our participants initially how defaults are set. There is considerable evidence in the literature (e.g., from guessing games, Bosch-Domènech et al., 2002; Bhatia et al., 2021) that participants do take into account who they interact with. Specific to defaults, Altmann, Falk and Grunewald (2022) explore the extent to which defaults can influence behavior in an environment where defaults provide signals about the state of the world and where the default setter's and decision makers' preferences may be partially misaligned. They show that in this setting, (i) decision makers take their strategic environment into account and (ii) default effects are less pronounced in cases where the interests of the default setter and decision maker are more misaligned. Thus, there is an a-priori reason that buyers' awareness of sellers' motive may influence their search behavior.[1]

To evaluate whether awareness of wicked defaults influences behavior, we ran a parallel set of treatments where we informed participants explicitly about whether the default was random or set by a profit-maximizing firm. Our theoretical model predicts that the decision maker accepts the default even if the preferences of parties are known to be fully misaligned. Thus, in contrast to Altmann, Falk and Grunewald (2022), we predict that default-accepting behavior in our setting is not affected by information regarding the motives of the default setter. Consistent with this prediction, we do not find strong evidence that the knowledge of the firm's profit-maximizing motive in default setting affects buyers' behavior. As such, sellers continue to benefit from wicked defaults when search costs are high even when their motivations are revealed.

Related literature: Our paper is related to the broader literature on defaults and the issues of misaligned incentives and information acquisition. Related to the issue of misaligned incentives, Gigerenzer (2015) provides a number of examples of potentially misaligned incentives in the health-care environment where practitioners order tests or recommend procedures due to concerns over their own liability (e.g., Studdert et al., 2005) or the revenue the procedures generate (e.g., Gøtzsche and Jørgensen, 2013; Woloshin and Schwartz, 2012; Gigerenzer, Mata and Frank, 2009). In economics, Altmann, Falk and Grunewald (2022) explore how defaults might be used to shape decisions in environments where incentives are potentially misaligned and where defaults convey information about the underlying state of the world. Dobrescu et al. (2016) explore empirically how defaults in plans and invest-

[1] Brown and Krishna (2004) and Campbell (2007) also find that decision makers alter their response to the default based on their beliefs about the default setter.

ment allocations influences wealth accumulation in a superannuation setting and highlight sub-optimal default recommendations. Ortmann et al. (2022) explore how defaults might be used to nudge individuals into insurance contracts when the seller has an informational advantage about customers' true risk.

The issue of information acquisition and nudge policies has also been discussed in the economics literature in settings where the choice architect is benevolent. Carlin, Gervais and Manso (2013) explore how defaults offered by a benevolent planner can reduce the information collected by individuals in the context of investment plans. The paper emphasizes how defaults may lead to information externalities when individuals can observe the investment plans selected by others. Caplin and Martin (2017) provide experimental evidence that the introduction of defaults causes decision makers to "drop out" of the decision process and accept the default without deliberation. We add to the literature by explicitly exploring the exploitative use of defaults by profit-maximizing firms and showing how these defaults can reduce consumer welfare even in single-person decision problems where there are no information spillovers.

Our paper is also related to the literature on consumer search (for a review see, e.g., Lippman and McCall, 1976; Ratchford, 2009), and optimal stopping problems more generally (e.g., Rapoport, Seale and Spiliopoulos, 2022). Our model is a variation of the early models of sequential search (McCall, 1970; Weitzman, 1979), in which the decision maker searches as long as the expected benefit of one additional search exceeds the marginal search cost, and the optimal stopping rule is based on a reservation value. Parallel strands of literature consider non-sequential, or fixed sample size, search where the decision maker first decides how many options to sample and then chooses the best one among those (Stigler, 1961), and variable sample size search, which is a generalization of the other two (Morgan and Manning, 1985). In combination with price competition, these models have been used to explain price dispersion in markets for homogeneous products (e.g., Stahl, 1989; Burdett and Judd, 1983). A number of empirical studies using natural market search data, including online search, have tried to identify which of the search algorithms better explains behavior, with mixed results (e.g., Hong and Shum, 2006; De los Santos, Hortaçsu and Wildenbeest, 2012).

The early experimental economics literature on search focused mostly on testing sequential-search models (Schotter and Braunstein, 1981; Grether, Schwartz and Wilde, 1988) as well as comparing potential search algorithms (Harrison and Morgan, 1990; Davis and Holt, 1996; Sonnemans, 1998; Cason and Friedman, 2003). Generally, the observed behavior in these studies is consistent with predicted comparative statics but deviates from the predictions of optimal sequential search. Subjects tend to search less than predicted, and the (imputed) reservation value declines with the number of searches, which is consistent with sunk-cost fallacy or elements of a fixed-sample size approach to search. Prices also tend to be lower than predicted, i.e., sellers do not fully exploit their informational advantage.[2] Gabaix et al. (2006) explored search in more complex settings where option values are drawn from different distributions and are obtained by aggregating multiple attributes (in the latter case, the fully optimal search algorithm is too complex to be derived). They find that a boundedly rational "direct cognition" search heuristic explains subjects' behavior well, and better than the fully optimal solution when it is available.

The introduction of a default implies that options in our environment are not sampled in a uniformly random way. As such, there are links between our paper and the literature on ordered search (Arbatskaya, 2007; Armstrong, 2017). The ordered-search literature explores buyer search behavior and firm competition in environments where buyers use characteristics such as location, advertisement recall, or observed prices to guide the order in which they search over options (Armstrong, 2017).[3] A main interest in this literature is the question of how firms set prices when consumers have heterogeneous valuations (Armstrong, 2017) or search costs (Arbatskaya, 2007; Armstrong, Vickers and Zhou, 2009; Xu, Chen and Whinston, 2010).

Our paper links the default literature to the ordered-search literature. Distinct from the ordered-search literature, our setting can be interpreted as the decision problem of a multi-product intermediary who is fully informed about the search cost of the consumer and who can alter the default but not influence the price-quality characteristics of each offering. This is common in environments where an informed intermediary, such as a broker, is offering products to clients and where the broker may receive product-specific bonuses.[4] Our interest is in understanding how consumer welfare is affected by defaults and empirically

[2] Similar results have also been obtained by Ryvkin, Serra and Tremewan (2017) and Ryvkin and Serra (2019, 2020) in their experiments on competition among corrupt public officials demanding bribes from citizens who could search for lower bribes across multiple offices, and by Cason and Datta (2006) and Cason and Mago (2010) in their experiments on costly search where sellers could advertise prices (at a cost), and where excessive advertisement was found.

[3] A subset of this literature studies environments where firms strategically order search. For example, Armstrong and Zhou (2011) study cases where competing firms can pay for prominence via commission or advertising while Varian (2007), Athey and Ellison (2011) and Chen and He (2011) study position auctions for websites.

[4] This broker interpretation of our seller is related to the work of Janssen and Williams (2021) who consider consumer search in a market with an influencer recommending products to consumers. The influencer's incentives are not fully aligned with those of consumers, and firms pay the influencer to recommend their product. The influencer samples some number of firms and recommends the one that gives her the highest value, effectively offering a default. Consumers then examine the recommended firm and buy its product if it is good enough, and search otherwise. In the environment considered in Janssen and Williams (2021), it is shown that consumers' welfare is increased by the presence of the influencer even when incentives are misaligned, because it is optimal for the influencer to recommend high quality products. Our paper studies an environment where defaults can improve or hurt consumer welfare depending on search cost.

exploring search behavior with wicked defaults. Similar to the existing literature (Wilson, 2010; Armstrong and Zhou, 2011; Armstrong, 2017), our results imply that firms have an incentive to damage the product environment by driving up search costs since this increases the set of potential products that fall within the buyers' acceptance set.

The role of defaults in settings with restricted search is also studied in the behavioral industrial organization literature on the impact of bounded rationality on competition (Spiegler, 2011, 2016). Spiegler (2015) explores how the default policy chosen by regulators influences obfuscation in an environment first studied by Varian (1980) where firms compete on price but can endogenously influence the comparability of choices by either (i) investing in obfuscation (Carlin, 2009; Chioveanu and Zhou, 2013) or (ii) selecting a pricing format that limits comparability (Piccione and Spiegler, 2012). He shows that firms' incentives to obfuscate can be strongly influenced by the default policies set by regulators.

Finally, we note a relation of our model to the model of manipulated attention by Gossner, Steiner and Stewart (2021). In their model, a decision maker receives a sequence of signals about multiple items by focusing attention on, and updating beliefs about, one item at a time. The authors show that for a wide class of attention allocation strategies, i.e., rules by which the decision maker switches attention from one item to the next, manipulating attention by focusing it initially on a particular item unambiguously raises the likelihood of that item being selected.[5] Default setting in our model can then be viewed as an attention manipulation where the seller-preferred (and incentive-compatible) item is placed at the start of the decision maker's consideration sequence. Trivially, that item is then selected with probability one by a payoff-maximizing decision maker.

The rest of the paper is structured as follows. In Section 2 we develop our theoretical model and discuss its comparative statics. Our experimental design is provided in Section 3, and the results are presented and discussed in Section 4. Section 5 concludes.

2 The model

A risk-neutral buyer faces a finite set of $n \geq 2$ options indexed by $i = 1, \ldots, n$, where each option i yields her a benefit b_i. The buyer does not observe the benefits initially, but believes they are i.i.d. draws from a known distribution $F(\cdot)$ with support $[\underline{b}, \overline{b}] \subseteq \mathbb{R}_+$. For simplicity, we assume throughout this section that F is absolutely continuous, with a bounded density $f(\cdot)$.

[5]The marketing literature has documented the importance of location in the selection of goods offered by profit-maximizing firms, which is likely related to attention. For example, Chandon et al. (2009) show that changing the location of products influences their demand while Atalay, Bodur and Rasolofoarison (2012) find that horizontal product placement increases demand but does not change beliefs about product quality.

The buyer's goal is to select one option. She starts a search process by (costlessly) considering option 1 and finding out about b_1; at this point the buyer may stop and select option 1 as her final choice, or continue searching and consider option 2, etc. Every additional search costs $c > 0$. We assume perfect recall: The buyer remembers the benefits of all previously encountered options and can costlessly go back to select any of them.

The setup follows a standard sequential search model (see, e.g., McCall, 1970; Weitzman, 1979). The optimal search strategy for the buyer is to search until the best available option has a value greater or equal to a reservation value, $z^*(c)$, determined by the condition

$$\int_z^{\bar{b}} (b - z) \mathrm{d}F(b) = c. \tag{1}$$

The left-hand side of (1), which can be written as $\mathbb{E}(\max\{b-z, 0\})$, is the expected benefit of one additional search given the best option encountered so far is $z \in [\underline{b}, \bar{b}]$, and the right-hand side is the cost of one additional search.

It is easy to see that the left-hand side of (1) is a strictly decreasing function of z that changes between zero for $z = \bar{b}$ and $\bar{c} \equiv \mathbb{E}(b) - \underline{b}$ for $z = \underline{b}$. Thus, a nontrivial reservation value will exist, and the buyer will search with positive probability, if $0 < c < \bar{c}$, which is an assumption we maintain throughout. It also follows that $z^*(c)$ is a strictly decreasing function of c in this range.

We consider two settings. In the first one, referred to as *random default* (RD), the ordering of options is random. The second setting we consider is referred to as *wicked default* (WD). Suppose there is a seller who observes the realization of the benefits $(b_1, \ldots, b_n)$ and can, unbeknownst to the buyer, designate any of the options as option 1—the starting point of search. In other words, the seller is able to set a default.

Which option will the seller choose as default? Let Π_i denote the seller's profit if the buyer selects option i. Further, let $A = \{i : b_i \geq z^*(c)\}$ denote the (possibly empty) set of options with benefits above the reservation value.

Proposition 1 *If $A \neq \varnothing$, a default $d \in \arg\max_{i \in A} \Pi_i$ is profit-maximizing.*

Indeed, since any option in A will be accepted without further search, setting d as the default will *always* be profit-maximizing.[6] Note that it is possible for other defaults to be profit-maximizing as well in some cases. Suppose, for example, that $d = 2$ but $1 \notin A$. Then the

[6] We continue to assume that the buyer is unaware of the seller choosing the default. This has three consequences. First, when A is empty, the seller cannot credibly communicate this information to the buyer through the default that is offered. This implies the seller is indifferent among all defaults and the buyer will search through all options and select the best option. This assumption is inconsequential when the number of options is sufficiently large because the probability that A is empty, $F(z^*(c))^n$, converges to zero as $n \to \infty$ (see also footnote 8). Second, the seller cannot deter search by adversely ordering the remaining options so

seller does not need to change anything: The buyer will consider option 1, search once, and buy option 2 anyway. More generally, as long as the buyer searches optimally, if d is preceded by any sequence of options outside of A, the seller's profit will be the same. However, d is uniquely *robust* in that it remains an optimal default in all possible scenarios. It is also an (almost surely) unique *best* seller-optimal default for the buyer. Since the seller cannot do better for herself and can only do worse for the buyer by choosing a default other than d, in what follows we assume that d is chosen as the optimal default.[7]

We will now explore the consequences of optimal default setting. There are two competing effects for the buyer's welfare: the optimal default helps her save on search costs but may preclude finding really good options. The latter effect becomes larger the more the seller's profits and the buyer's benefits are misaligned. To simplify matters, we consider an extreme case of fully misaligned incentives.

Assumption 1 *All options $i = 1, \ldots, n$ have a fixed total surplus S such that $b_i + \Pi_i = S$.*

Under the fixed surplus assumption, the seller would like the buyer to choose the option with the lowest possible benefit; therefore, the optimal default is simply $d \in \arg\min_{i \in A} b_i$. Omitting the argument of z^* for brevity, the buyer's expected payoff under optimal default is

$$\pi_{\mathrm{WD}} = \int_{\underline{b}}^{z^*} b \mathrm{d}F(b)^n - F(z^*)^n c(n-1) + \sum_{k=1}^{n} \binom{n}{k} F(z^*)^{n-k} [1 - F(z^*)]^k \int_{z^*}^{\bar{b}} b \mathrm{d}\tilde{F}_{(1:k)}(b), \quad (2)$$

where (i) function $\tilde{F}(b) = \frac{F(b) - F(z^*)}{1 - F(z^*)}$ is the updated distribution of benefits above z^* and (ii) function $\tilde{F}_{(1:k)}(b) = 1 - (1 - \tilde{F}(b))^k$ is the distribution of the lowest order statistic among k i.i.d. draws from $\tilde{F}$. The first two terms of (2) represent the expected payoff if $A = \varnothing$; the buyer will search $n - 1$ times in this case and select the best option. The third term is the expected payoff when $A \neq \varnothing$. The sum is over $k = |A|$. For each possible k, the default is set at (and the buyer selects, without searching) the option with the lowest benefit above z^*.

that the buyer must search through bad options before reaching one that improves upon the default. Third, the buyer does not update her beliefs about the distribution of options after she observes the default. A fully rational buyer who is aware of how the default is set would realize there is a gap in the distribution of values between $z^*(c)$ and b_1, and would update her search strategy accordingly. However, as we show in Appendix B, such updating does not lead to additional search for value distributions that have an increasing hazard rate, which holds in our experiment.

[7] From a behavioral viewpoint, considering incentives outside our model, default d is (almost surely) uniquely optimal for a seller who cares, in a lexicographic manner, about the buyer's welfare alongside the seller's own. This is especially important in settings with repeated interactions where the seller may be interested in cultivating the buyer's trust.

The buyer's payoff in the random default setting can similarly be written as

$$\pi_{\text{RD}} = \int_{\underline{b}}^{z^*} b \mathrm{d}F(b)^n - F(z^*)^n c(n-1) + \sum_{k=1}^{n} \binom{n}{k} F(z^*)^{n-k}[1-F(z^*)]^k \left[\int_{z^*}^{\bar{b}} b \mathrm{d}\tilde{F}(b) - cs_k\right], \quad (3)$$

where, as before, $\tilde{F}(b)$ is the updated belief distribution of benefits above z^* and s_k is the expected number of searches for a given k. The first two terms are the same as in (2) and correspond to $A = \varnothing$. The third term is again written as a sum over $k = |A|$, but this time the buyer's expected payoff for a given k is the expectation of b above the reservation value less the expected search cost.

The following lemma provides a simplified expression for s_k.

Lemma 1 *The expected number of searches for a given $k = |A| \geq 1$ is*

$$s_k = \frac{n-k}{k+1}. \quad (4)$$

We include the proof of Lemma 1 and all other omitted proofs in Appendix A. We note here that s_k is decreasing in k. Further, as expected, zero searches are needed when $k = n$.

Comparing (2) and (3), we can write the difference in the buyer's payoff between the optimal default and baseline settings as

$$\begin{aligned} \pi_{\text{WD}} - \pi_{\text{RD}} &= cF(z^*)\left[\frac{1-F(z^*)^n}{1-F(z^*)} - nF(z^*)^{n-1}\right] \\ &- \sum_{k=1}^{n} \binom{n}{k} F(z^*)^{n-k}[1-F(z^*)]^k \int_{z^*}^{\bar{b}} (\tilde{F}_{(1:k)}(b) - \tilde{F}(b))\mathrm{d}b. \end{aligned} \quad (5)$$

To obtain the first term, we used (4) and summed up a binomial series. The second term is obtained by combining (2) and (3) and integrating by parts.

The two terms in (5) represent the two competing effects of the optimal default described previously. Both effects are zero in the absence of search costs. The first term is the savings on search costs and is proportional to c. Importantly, even though it is positive when c is small, it tends to zero when c approaches $\bar{c}$ because $z^*(c)$ approaches $\underline{b}$. The second term is the loss in expected benefits due to the optimal choice of default. It arises due to first-order stochastic dominance between $\tilde{b}$—a random benefit above the reservation value, and $\tilde{b}_{(1:k)}$—the lowest order statistic among k draws of such benefits. This effect is zero for $c = 0$ and increasing in c. Indeed, as c rises, $z^*(c)$ falls and hence the terms with higher values of k contribute more to the sum. But larger values of k—the number of options above the reservation value—produce stochastically larger differences in benefits $\tilde{b} - \tilde{b}_{(1:k)}$. In general, while the difference $\pi_{\text{WD}} - \pi_{\text{RD}}$ may depend on c in a complicated way determined by the shape of F, we show that it is always positive for low enough c and negative for high enough c. Formally, the result is as follows.

Proposition 2 *When Assumption 1 holds, there exist search costs $c_L, c_H \in (0, \bar{c})$ such that $\pi_{\text{WD}} < \pi_{\text{RD}}$ for all $c \in (c_H, \bar{c}]$ and $\pi_{\text{WD}} > \pi_{\text{RD}}$ for all $c \in (0, c_L)$.*

We note that the seller is always weakly better off in offering a default since the seller can select a profit-maximizing option in A. Moreover, if $|A| > 1$ with positive probability, the seller is strictly better off in expectation. Further, when total surplus is fixed and preferences are fully misaligned, the seller's additional profit from optimal default setting is strictly increasing in c. This can be seen by noting that the extra surplus extracted by the seller is exactly the second term in (5), and this term is strictly increasing in c as explained above.

Corollary 1 *When Assumption 1 holds, the seller's additional profit from optimal default setting is strictly increasing in c.*

Finally, we acknowledge that sequential search is not the only possible search algorithm, and it may be of interest to what extent the results of this section are robust to variation in search strategies. In Appendix C, we consider an alternative model—fixed sample size search, where buyers observe the default option, b_1, and commit to a fixed number of options $s(b_1)$ they would like to reveal, at cost $cs(b_1)$. We show the existence of a generically unique optimal strategy, $s^*(b_1)$, and find that under the optimal wicked default identified in this section (i.e., based on the reservation value $z^*(c)$), a result similar to Proposition 2 continues to hold. The main reason is that $s^*(b_1) = 0$ for any $b_1 > z^*(c)$, i.e., such defaults shut down fixed sample size search as well.

3 The experiment

We implemented a 2×2×2 design in which we generated within-subject variation in the way that defaults were assigned and between-subject variation in the cost of search. We conducted this basic 2×2 design as is; we also informed participants—in an otherwise identical duplicate of the basic 2×2 design—whether the initial offers were random or put forward by a profit-maximizing seller. Across sessions, individuals were assigned to either a **High Cost (HC)** environment or a **Low Cost (LC)** environment. Within a session, subjects played a total of 80 rounds, 40 of which were randomly assigned to a **Random Default (RD)** round and the remaining rounds were assigned to a **Wicked Default (WD)** round; these round assignments were pre-drawn and followed the same sequence for all subjects in all sessions.

As mentioned above, we also duplicated this baseline 2×2 design by informing the participants about how the initial offers were chosen in each round. Specifically, in RD rounds participants were told that the initial offers were random, and in WD rounds they were told that "*The seller has selected the lowest offer that it believes you will accept without searching.*" We refer to this condition as the **Announcement (A)** condition, and to the baseline condition as **No Announcement (NA)**. We refer to our experimental sessions as **HC-NA**, **HC-A**, **LC-A**, or **LC-NA** because subjects within a session play rounds with both a wicked default and a random default. A treatment cell in our design is denoted as **HC-RD-NA**, **HC-WD-NA**, **LC-RD-NA**, **LC-WD-NA**, **HC-RD-A**, **HC-WD-A**, **LC-RD-A**, or **LC-WD-A**.

Parameters of the experiment and theoretical predictions are summarized in Table 1 for treatments using the no-announcement condition. The corresponding announcement conditions have identical parameters and predictions. We set total surplus to $S = 100$ and follow Assumption 1 that buyers' and sellers' incentives are fully misaligned, i.e., if a buyer chooses an option with benefit b, the seller's profit is $100 - b$. The distribution of benefits is uniform on $[0, 100]$. Search costs are set to $c = 30$ and $c = 5$ in the HC and LC environments, respectively.

We conducted two pilot sessions, one for HC-NA with 11 subjects and the other for LC-NA with 13 subjects, and performed a power analysis based on the effect size of the WD treatment for subjects' payoffs. We obtained Cohen's $d = 2.04$ in HC and $d = 0.72$ in LC, indicating "huge" and "medium" effect sizes, respectively, following the classification of Sawilowsky (2009). The corresponding number of subjects based on a power calculation for paired data with $\alpha = 0.05$ and $\beta = 0.1$ produced $N = 5$ and $N = 23$ for HC and LC, respectively. Therefore, conservatively, we targeted our recruitment to collect data from 30 subjects per treatment cell.

For each subject, we used a pre-drawn 80-round sequence of decision problems. To maximize parallelism, we generated 30 different sequences for 30 subjects and re-used them in all treatments. Each decision problem was generated in two steps. First, we generated 10 "cards" by randomly drawing an integer value uniformly on $\{0, 1, \dots, 100\}$. Next, we assigned one of the cards to be the initial offer and arranged the remaining 9 cards in a random sequence. The way that the initial offer card was selected differed by treatment. In RD rounds, each card had an equal chance of being assigned as the initial offer. In WD rounds, we assigned the card with the lowest value in the interval $[z^*(c), 100]$ to be the initial

Table 1: Parameters, theoretical predictions, and number of subjects in the no announcement treatments of the experiment.

Treatments	Search Cost, c	Cutoff, $z^*(c)$	# of Searches	Buyer's Payoff	Seller's Payoff	Subjects
LC-RD-NA	5	68.4	2.09	73.2	16.3	30
HC-RD-NA	30	22.5	0.29	52.5	38.7	30
LC-WD-NA	5	68.4	0.20	75.5	23.5	30
HC-WD-NA	30	22.5	0.00	31.6	68.4	30

Values in the experiment are drawn from a uniform distribution on $[0, 100]$ in each treatment cell, and the total surplus is set to $S = 100$ tokens. Note that theoretical predictions are the same for the no-announcement and announcement conditions.

offer.[8]

Subjects in each round were endowed with 200 tokens and were shown the value of the card containing the initial offer. They then had the option of "accepting the best offer" and ending the period or paying to reveal the next card in the sequence. Revealing an additional offer incurred a fixed cost of 5 tokens in the LC environment and 30 tokens in the HC environment. The participant could continue to reveal cards until either all cards were revealed or they chose to accept the best offer.

Throughout a round, the computer automatically highlighted the card containing the best offer and the value of this card was prominently displayed. Subjects also were shown the total cost of previous searches and the payoff that the subject would receive if they accepted the best offer at that point.

We pre-registered the experiment on the Wharton Credibility Lab AsPredicted platform under #96405 (the baseline 2×2 design) and #96863 (the announcement condition).

3.1 Experimental protocols

All of the sessions were run online with participants from the pool of pre-registered student subjects at the Behavioural Lab of the University of Technology Sydney in May of 2022. The experiment was implemented using the programming language oTree (Chen, Schonger and Wickens, 2016). A total of 120 subjects participated in 7 sessions. All subjects were recruited from the subject pool using ORSEE (Greiner, 2015).

Individuals were provided with instructions (see Appendix D) which described the search game and included a quiz that required the subject to identify the best offer and the cost of search from a hypothetical round where the participant searched three additional

[8]Following the model, we randomly selected a default if the acceptable offer set was empty. The probability of this occurring for a given subject in any given round is $F(z^*(c))^n = 3.39 \times 10^{-7}$ in the HC environment and 0.0223 in the LC environment.

times. After successfully completing the quiz, subjects then played through the 80 rounds of the search game in a fixed order.

After the main experiment, subjects participated in three additional lottery tasks where subjects' risk aversion, loss aversion and ambiguity aversion were elicited using list methods. In each of these tasks, subjects were presented with a list of 21 choices between a lottery and a sure amount of money. Each list was constructed so that if a subject's preference respected monotonicity, there was a unique point at which they were willing to switch from the lottery to the sure amount. In the risk task, individuals chose between a lottery $(0, \$2.00; 0.5, 0.5)$ and a sure amounts of money that increased from zero to \$2.00 in 10 cent increments. In the loss task, the lotteries were $(-\$x, \$2.00; 0.5, 0.5)$, where x changed from 0 to 2.00 in 10 cent increments, and the sure amount of money was always 0. Finally, in the ambiguity task the lottery was $(0, \$2.00; p, 1-p)$, where, unbeknownst to subjects, p was generated randomly from the uniform distribution on $[0, 1]$, and the sure amounts were the same as in the risk task. The three tasks were presented to subjects in a random order, without feedback, and one of them was randomly selected for actual payment.

We randomly selected 4 rounds from the search game and one of the three lottery tasks for payment. Participants were informed about this earnings mode. Subjects were paid 1 AUD for every 100 tokens they earned in those rounds as well as an additional 5.00 AUD show-up payment. On average, participants spent about 35 minutes completing the experiment and earned 15.86 AUD.

3.2 Hypotheses

The following hypotheses are based on the model predictions summarized in Table 1. We formulate hypotheses in the form of comparative statics, as opposed to point predictions, because subjects are likely to deviate from payoff-maximizing search behavior, and our interest is in how robust the model predictions are to such deviations.

Our experimental design generates between-subject variation in costs (LC or HC), within-subject variation in defaults (RD or WD), and between-subject variation in announcements (NA or A). We first describe our hypotheses related to the cost dimension since strong deviations in this dimension would make it more difficult to understand how behavior is influenced by the default.

Hypothesis 1 *Search is lower in the HC environment than in the LC environment in RD rounds but not in WD rounds. Buyers' profits are decreasing in costs regardless of how the default is set. Likewise, sellers' profits are increasing in costs regardless of how the default is set.*

The first part of this hypothesis follows the comparative statics of search behavior. For subjects using the reservation value stopping rule, the lower bound of the acceptance set falls as costs increase. As such, we would predict more search when defaults are random and costs are low relative to the case where defaults are random and costs are high. In wicked-default rounds, the default has been set to prevent search in both the high-cost and low-cost treatments, and thus there is no predicted difference in search except for the rare case where all options happen to be below the reservation value.[9]

An increase in search costs will influence the default offered in WD rounds and reduce search in RD rounds. As both of these responses will lead to lower-valued options being selected, buyers' payoffs are predicted to be decreasing in search costs and sellers' payoffs are predicted to be increasing in search costs.[10]

We next turn to our comparative static predictions with relation to the way that defaults are set. We have three hypotheses related to the comparison of the random-default treatments and wicked-default treatments:

Hypothesis 2 *Search in WD rounds is lower than in RD rounds in both the LC and HC environments.*

Hypothesis 3 *Buyer's payoffs are lower in WD rounds than in RD rounds in the HC environment. In the LC environment, the opposite holds.*

Hypothesis 4 *Firm's profits are higher in WD rounds than in RD rounds in both the LC environment and the HC environment.*

Hypothesis 2 follows directly from the choice of the wicked default, which is predicted to always prevent further search except in a small number of cases under LC. Hypothesis 3 is based on our choice of parameters for the high-cost and low-cost environments. We selected $c = 5$ for the low-cost environment since this cost was in the range where buyers benefit from wicked defaults, and $c = 30$ for the high-cost environment since this is in the range of costs where the buyers are predicted to be worse off. The former effect is relatively small, as discussed in Section 2.

Hypothesis 4 is due to the assumption that buyer and seller preferences are perfectly misaligned and the fact that the wicked default is selected to be the lowest option that is

[9] This occurs in 2% of cases in the LC treatment and never occurs in the HC treatment. These proportions are similar to the theoretical proportions discussed in footnote 8.

[10] The expected search cost paid in the low-cost random-default rounds is 10.46 while the expected search cost paid in the high-cost random-default rounds is 8.73. As such, the difference in search costs is small and the comparative statics in buyers' payoffs is driven primarily by lower-valued options being selected in the high-cost environment.

in the buyer's acceptance set. Since this is always lower than the average acceptable option in expectation, the seller is predicted to be better off under the wicked default regardless of the cost of search.

Finally, we turn to our hypothesis regarding announcements.

Hypothesis 5 *Announcements putting buyers potentially on alert about the motives of the sellers do not have an effect.*

As discussed in the Introduction, there may be reasons for subjects to react to the information on default setting; therefore, the alternative hypothesis is that some buyers may be upset about wicked default and search more than predicted in order to unwind the default. If that is the case, we would predict that buyers' payoffs and the firm's profit would be negatively affected.

4 Results

We start our analysis with an overview of the data, a comparison of the treatments to their point predictions, and the comparative statics related to costs. Table 2 reports summary statistics for each of the eight treatment cells alongside the theoretical point predictions, which are reproduced from Table 1 for convenience.

One general finding across all treatments is that subjects search too much as compared to the average optimal number of searches. The difference is statistically significant in all treatment conditions except LC-RD-A, where average search intensity is almost exactly optimal. Importantly, subjects search substantially in rounds with wicked defaults. This is in contrast to the theoretical prediction that search should only occur in the wicked default rounds when all options fall below the reservation value (which, as noted in footnote 8, is very unlikely). These deviations from optimal search behavior have consequences for subjects' payoffs and the firm's profit with both the buyers' payoffs and the firms' profits generally lower than predicted under optimal search.

Despite the abundance of search, the comparative statics with respect to costs are all strongly consistent with theory.

Result 1 *Consistent with Hypothesis 1, subjects search less in the HC environment than in the LC environment in RD rounds, but in WD rounds there is no difference. Buyers' profits are lower in the HC environment than in the LC environment while sellers' profits are higher in the HC environment than in the LC environment.*

Support for the first part of Result 1 is based on nonparametric Wilcoxon rank-sum tests shown in Panel A of Table 3. To perform these tests, we calculated the average number of searches in RD rounds and in WD rounds for each subject and treat the two treatments as separate samples.[11] As seen in the panel, search is significantly lower in the HC treatment than the LC treatment for RD rounds, but there is no significant decrease in search in WD rounds.

We use the same nonparametric Wilcoxon rank-sum test to assess buyers' payoffs and sellers' profits. As seen in Panel B, buyers' profits are significantly lower in all four pair-wise comparisons of the LC environment and the HC environment. Likewise, as seen in Panel C, the sellers' profits are significantly higher in all four pair-wise treatment comparisons.

Table 2: Summary statistics, with robust standard errors clustered by subject in parentheses, and theoretical predictions.

Treatments	# of searches		Buyer's payoff		Seller's profit		Subjects
	data	theory	data	theory	data	theory	
LC-RD-NA	2.51	2.09	68.84	73.24	18.60	16.30	30
	(0.22)		(0.81)		(1.02)		
HC-RD-NA	1.08	0.29	37.08	52.54	30.54	38.73	30
	(0.12)		(2.64)		(1.57)		
LC-WD-NA	1.76	0.20	72.61	75.48	18.61	23.52	30
	(0.28)		(0.84)		(0.82)		
HC-WD-NA	1.51	0.00	16.74	31.63	38.01	68.37	30
	(0.14)		(2.42)		(2.35)		
LC-RD-A	2.08	2.09	67.20	73.24	22.43	16.30	30
	(0.16)		(1.29)		(1.80)		
HC-RD-A	1.16	0.29	34.31	52.54	30.91	38.73	30
	(0.20)		(5.04)		(1.57)		
LC-WD-A	1.49	0.20	73.14	75.48	19.39	23.52	30
	(0.22)		(0.64)		(0.67)		
HC-WD-A	1.58	0.00	13.31	31.63	39.41	68.37	30
	(0.23)		(5.07)		(2.70)		

Summary statistics from the 8 treatments that result from the $2 \times 2 \times 2$ design. Treatments are divided into Low Cost (LC) or High Cost (HC) environments, Random Default (RD) or Wicked Default (WD) rounds, and No Announcement (NA) or Announcement (A) conditions.

[11] We, however, do not compare RD rounds and WD rounds to each other at this point; rather, we compare RD rounds to RD rounds and WD rounds to WD rounds across the two cost environments, i.e., between subjects.

Table 3: Statistical Tests for Hypothesis 1

Panel A: Comparison of Search by Search Cost					
Treatments Compared	z-score	p-value	N_1	N_2	Statistical Test
LC-RD-NA vs HC-RD-NA	4.89	< 0.01	30	30	Wilcoxen Rank-Sum
LC-WD-NA vs HC-WD-NA	0.07	0.95	30	30	Wilcoxen Rank-Sum
LC-RD-A vs HC-RD-A	4.09	< 0.01	30	30	Wilcoxen Rank-Sum
LC-WD-A vs HC-WD-A	-0.27	0.79	30	30	Wilcoxen Rank-Sum
Panel B: Comparison of Buyers' Payoff by Search Cost					
Treatments Compared	z-score	p-value	N_1	N_2	Statistical Test
LC-RD-NA vs HC-RD-NA	6.65	< 0.01	30	30	Wilcoxen Rank-Sum
LC-WD-NA vs HC-WD-NA	6.65	< 0.01	30	30	Wilcoxen Rank-Sum
LC-RD-A vs HC-RD-A	6.37	< 0.01	30	30	Wilcoxen Rank-Sum
LC-WD-A vs HC-WD-A	6.65	< 0.01	30	30	Wilcoxen Rank-Sum
Panel C: Comparison of Sellers' Profits by Search Cost					
Treatments Compared	z-score	p-value	N_1	N_2	Statistical Test
LC-RD-NA vs HC-RD-NA	-5.10	< 0.01	30	30	Wilcoxen Rank-Sum
LC-WD-NA vs HC-WD-NA	-6.17	< 0.01	30	30	Wilcoxen Rank-Sum
LC-RD-A vs HC-RD-A	-3.88	< 0.01	30	30	Wilcoxen Rank-Sum
LC-WD-A vs HC-WD-A	-5.77	< 0.01	30	30	Wilcoxen Rank-Sum

Statistical tests for Hypothesis 1. Panel A is a comparison of search; Panel B is a comparison of buyers' payoffs; Panel C is a comparison of sellers' profits. All tests are a nonparametric Wilcoxon rank-sum test with the two treatments treated as independent samples.

4.1 Comparison of the Wicked Default rounds and Random Default rounds

Having established that the comparative statics with respect to costs are consistent with theory, we now turn our attention to search under random and wicked defaults. We find mixed support for our second hypothesis:

Result 2 *Consistent with Hypothesis 2, subjects search more in RD rounds than WD rounds in the LC environment. However, in contrast to Hypothesis 2, the opposite is true in the HC environment.*

Figure 1 shows the average number of searches per round in each treatment. The top two panels show the treatments with no announcement, and the bottom two panels show

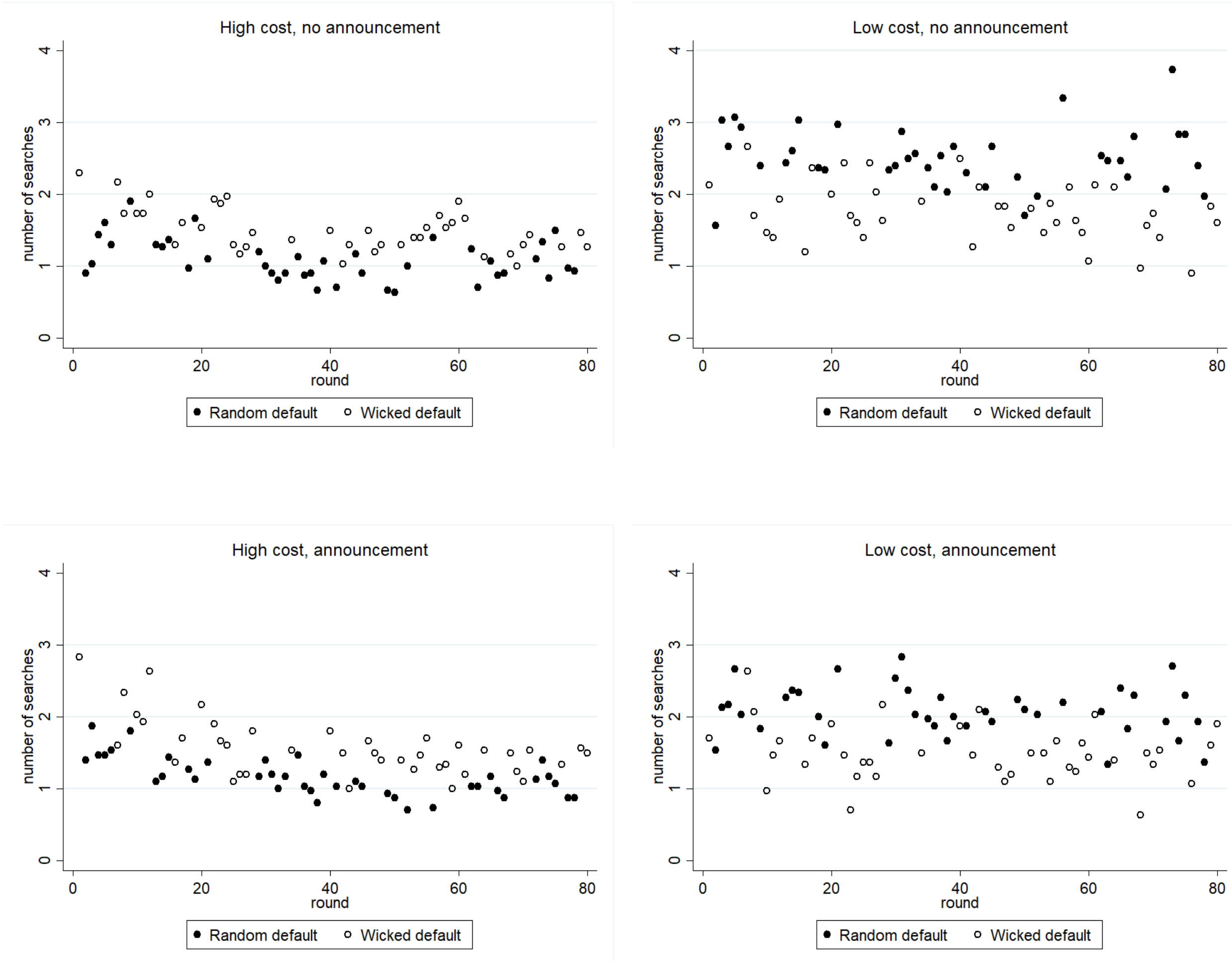

Figure 1: The average number of searches per round, by treatment.

the treatments with announcement. As seen from the figure, when the search cost is high, subjects consistently search more in rounds with wicked default than in rounds with random default; however, the opposite holds when the search cost is low. These patterns appear unchanged in the presence of the announcement (the bottom two panels). We also note that there is a small downward trend in search intensity in the high cost treatments (in pooled OLS regressions of the number of searches on round number, the slope estimates are -0.0052, $p = 0.011$, in HC-NA; -0.0081, $p = 0.003$, in HC-A; errors clustered by subject), but not in the low cost treatments. This behavior is transient: None of the treatments has a significant time trend when the first 10 rounds of the data are excluded. Following our pre-analysis plans, we use data from all rounds in all of the analysis.[12]

Further support for Result 2 is based on the nonparametric Wilcoxon matched pairs signed rank test. To perform this test, we calculated the average number of searches in

[12]Excluding the first 10 rounds does not materially affect any of our results.

RD rounds and in WD rounds for each subject. As seen in Panel A of Table 4, there is significantly more search in RD rounds than WD rounds in the LC treatment and there is significantly more search in WD rounds than RD rounds in the HC treatment.

To better understand the deviation in the HC treatment, we explored the cutoff rules employed by individual subjects in an ex-post analysis. For each subject, we plotted the distribution of values that were accepted in each of the 80 decision rounds. These values are an upper bound of what an individual's reservation value is since an individual is likely to be offered a value that is above their cutoff rule in each round. However, by finding the lowest value accepted over the 80 rounds (or a low quantile of this distribution), we can approximate a cutoff rule for each individual.

Figure 2 shows the distribution of cutoff rules when we use the lowest value in the distribution (left) or allow for some noise by using the the 10th percentile (right).[13] As seen in both sub-figures, buyers have heterogeneous cutoffs in the high-cost treatment and many use a cutoff rule that is between 30 and 50. By contrast, most buyers in the low-cost treatment have a cutoff near the theoretical value of 68.4 once a small amount of noise is accounted for.

We also investigated how the empirical cutoffs are related to the elicited risk aversion, loss aversion and ambiguity aversion measures, and did not find any significant correlations.

Since our theoretically predicted cutoffs are payoff-maximizing, the excessive search observed in the WD rounds leads to a decrease in payoffs relative to the theoretical predictions, especially in the HC treatment. Interestingly, it does not invalidate the predicted reversal of payoff comparisons between WD and RD rounds under high and low costs.

Result 3 *Consistent with Hypothesis 3, buyers' payoffs are lower in WD rounds than in RD rounds in the HC environment. In the LC environment, the opposite holds.*

Support for Result 3 is based on the same nonparametric Wilcoxon matched pairs signed-rank test that we used above with buyers' payoff as the variable of interest. As seen in Panel B of Table 4, buyers' payoffs are significantly higher in WD rounds than RD rounds in the LC treatment and significantly lower in WD rounds than RD rounds in the HC treatment.

[13] We also explored alternative specifications where we use the lowest value rejected by each buyer as their reservation value and a specification where we estimate each individual's reservation value using quantal response by finding the value where each individual is indifferent between accepting and rejecting the offer. We also looked at the cutoff rules reported in the questionnaire at the end of the experiment. The results from these alternative analyses are similar to the results shown here with (i) substantial dispersion in cutoff rules in the high-cost treatment and estimated or reported reservation values between 30 and 50 and (ii) less dispersed cutoff rules in the low-cost treatment with modal estimated or reported reservation values around 70.

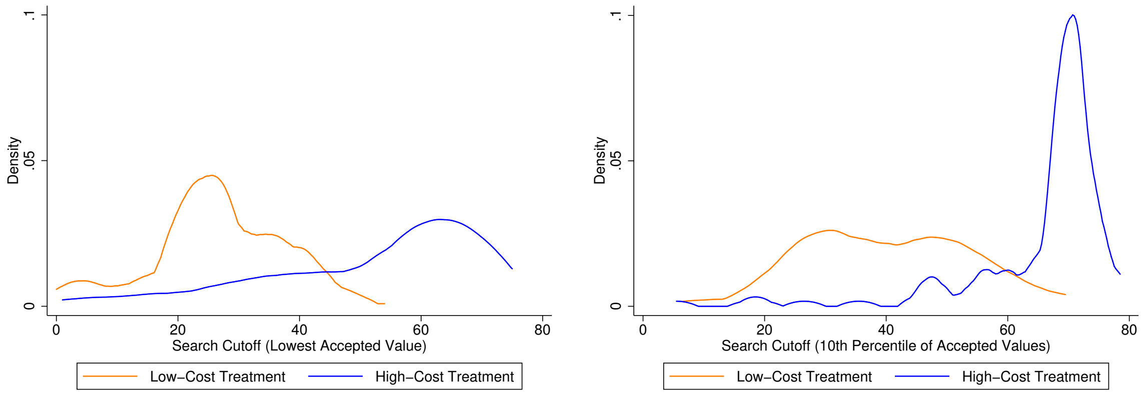

Figure 2: Epanechnikov kernel plots of the search cutoffs employed by buyers. Optimal bandwidth is used. The left panel uses the lowest offer accepted over all 80 rounds as the cutoff. The right panel uses the 10th percentile of accepted offers to allow for some noise in acceptance decisions.

Table 4: Statistical Tests for Hypotheses 2-4

Panel A: Comparison of Search by Default				
Treatments Compared	z-score	p-value	N	Statistical Test
LC-RD-NA vs LC-WD-NA	3.64	< 0.01	30	Sign-rank test
HC-RD-NA vs HC-WD-NA	-3.91	< 0.01	30	Sign-rank test
LC-RD-A vs LC-WD-A	3.16	< 0.01	30	Sign-rank test
HC-RD-A vs HC-WD-A	-4.28	< 0.01	30	Sign-rank test
Panel B: Comparison of Buyers' Payoff by Default				
Treatments Compared	z-score	p-value	N	Statistical Test
LC-RD-NA vs LC-WD-NA	-3.59	< 0.01	30	Sign-rank test
HC-RD-NA vs HC-WD-NA	4.68	< 0.01	30	Sign-rank test
LC-RD-A vs LC-WD-A	-3.48	< 0.01	30	Sign-rank test
HC-RD-A vs HC-WD-A	4.74	< 0.01	30	Sign-rank test
Panel C: Comparison of Sellers' Profits by Default				
Treatments Compared	z-score	p-value	N	Statistical Test
LC-RD-NA vs LC-WD-NA	-0.46	0.64	30	Sign-rank test
HC-RD-NA vs HC-WD-NA	-4.52	< 0.01	30	Sign-rank test
LC-RD-A vs LC-WD-A	1.39	0.17	30	Sign-rank test
HC-RD-A vs HC-WD-A	-4.54	< 0.01	30	Sign-rank test

Statistical tests for Hypotheses 2-4. Panel A is a comparison of search by default; Panel B is a comparison of buyers' payoffs by default; Panel C is a comparison of sellers' profits by default. All tests are a nonparametric Wilcoxon matched pairs signed rank test with RD rounds paired to WD rounds by individual buyer.

Finally, we look at sellers' profits. In both the HC treatment and LC treatment, buyers tend to search excessively in WD rounds, which tends to reduce overall seller's profits. In the HC treatment, the excessive search also occurs in the RD rounds and on net the seller is better off in the WD rounds relative to the RD rounds since a subset of buyers accept the wicked default. In the LC treatment, search is excessive in both cases and the sellers' profits are similar across treatments. These findings are summarized in the following result and the corresponding tests are shown in Panel C of Table 4.

Result 4 *Consistent with Hypothesis 4, seller's payoffs are higher in WD rounds than in RD rounds in the HC environment. However, there is no significant difference in sellers' profits between WD and RD rounds in the LC environment.*

4.2 Comparison of the Announcement and No-Announcement treatments

As the final part of the analysis, we explore whether awareness of wicked defaults influences behavior. Comparing our baseline No-Announcement treatments to the corresponding Announcement treatment, we find the following.

Result 5 *Consistent with Hypothesis 5, there are no significant changes in search, buyers' payoffs, or firms' profits when buyers are informed about the motives of the seller.*

Support for Result 5 is provided in Table 5 where we report Wilcoxon nonparametric rank-sum tests comparing each announcement treatment to the corresponding no announcement treatment.[14] As with the analysis of costs, we average the outcome variable to the individual level and compare the resulting treatment-level distributions.

As seen in Panel A of Table 5, there are no significant differences in search between the announcement treatments. Likewise, as seen in Panels B and C, there are no significant differences in buyers' payoffs or sellers' profits.

[14] An alternative test would be to pair the data by value sequence and perform a Wilcoxon nonparametric sign-rank test across the pairs. As with the tests reported here, we cannot reject the null in any of the 12 tests under this alternative specification.

Table 5: Statistical Tests for Hypothesis 5

Panel A: Comparison of Search by Announcement					
Treatments Compared	z-score	p-value	N_1	N_2	Statistical Test
LC-RD-NA vs LC-RD-A	1.27	0.20	30	30	Wilcoxen Rank-Sum test
LC-WD-NA vs LC-WD-A	0.34	0.73	30	30	Wilcoxen Rank-Sum test
HC-RD-NA vs HC-RD-A	0.49	0.63	30	30	Wilcoxen Rank-Sum test
HC-WD-NA vs HC-WD-A	0.59	0.55	30	30	Wilcoxen Rank-Sum test
Panel B: Comparison of Buyers' Payoff by Announcement					
Treatments Compared	z-score	p-value	N_1	N_2	Statistical Test
LC-RD-NA vs LC-RD-A	0.86	0.39	30	30	Wilcoxen Rank-Sum test
LC-WD-NA vs LC-WD-A	−0.10	0.92	30	30	Wilcoxen Rank-Sum test
HC-RD-NA vs HC-RD-A	−0.27	0.79	30	30	Wilcoxen Rank-Sum test
HC-WD-NA vs HC-WD-A	−0.51	0.61	30	30	Wilcoxen Rank-Sum test
Panel C: Comparison of Sellers' Profits by Announcement					
Treatments Compared	z-score	p-value	N_1	N_2	Statistical Test
LC-RD-NA vs LC-RD-A	−1.37	0.17	30	30	Wilcoxen Rank-Sum test
LC-WD-NA vs LC-WD-A	−0.47	0.64	30	30	Wilcoxen Rank-Sum test
HC-RD-NA vs HC-RD-A	0.04	0.97	30	30	Wilcoxen Rank-Sum test
HC-WD-NA vs HC-WD-A	−0.25	0.80	30	30	Wilcoxen Rank-Sum test

Statistical tests for Hypothesis 5. Panel A is a comparison of search; Panel B is a comparison of buyers' payoffs; Panel C is a comparison of sellers' profits. All tests are a nonparametric Wilcoxon rank-sum test with the two treatments treated as independent samples.

5 Conclusions

We proposed a simple model of how a profit-maximizing seller can benefit from strategically setting defaults in environments where buyers choose one of several available options whose values are initially unknown but can be discovered through costly search. We show that, theoretically, sellers always benefit from setting a wicked default and that the expected impact on buyers depends on search costs. Buyers with low enough search costs benefit from strategic-default setting because they economize on search and it is optimal for the firm to offer them high-quality defaults. However, high-cost buyers suffer because their defaults are inferior, yet good enough for them to refrain from searching. Wicked defaults hence prevent search theoretically.

We find that the main comparative statics of our model are realized in an experimental environment where we vary the way in which the default is set between rounds and the cost of search between individuals. Wicked defaults are indeed beneficial to buyers when search costs are low but harmful to buyers when search costs are high. However, in the high-cost treatments, buyers tend to search more than predicted and this leads to even worse outcomes for the buyers than our theoretical model would predict.

Our theoretical model is stylized, but the issue of sequential information acquisition in the context of a better-informed principal is quite general. Examples of such environments abound in industries where sellers of goods or services have asymmetric expertise. Such sellers include financial advisors, car mechanics, IT specialists, medical consultants, financial advisors, lawyers, real-estate agents, and contractors.

The negative consequences of wicked defaults are more severe the larger the search costs, and the more the incentives of buyers and seller are misaligned. To the extent search costs are correlated with characteristics such as age, cognitive ability, income or education, it appears that the most vulnerable segments of the population may be disproportionately affected.

Our results are rather pessimistic and suggest that wicked defaults may be an effective strategy for surplus extraction by monopoly sellers even when buyers' and sellers' incentives are known to be misaligned. Future research may consider richer environments involving multiple firms, to study the effects of competition, or the availability of feedback and information systems such as consumer ratings or product reviews, as possible mechanisms mitigating the negative impact of strategic default setting.

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A Proofs

Proof of Lemma 1 The expected number of searches for a given $k = |A| \geq 1$ is

$$\begin{aligned} s_k = &\frac{k}{n} \cdot 0 + \frac{n-k}{n} \cdot \frac{k}{n-1} \cdot 1 + \frac{n-k}{n} \cdot \frac{n-k-1}{n-1} \cdot \frac{k}{n-2} \cdot 2 \\ &+ \ldots + \frac{n-k}{n} \cdot \frac{n-k-1}{n-1} \cdot \ldots \cdot \frac{1}{n-k} \cdot \frac{k}{k} \cdot (n-k) = \sum_{l=0}^{n-k} \frac{(n-k)!(n-l)!}{(n-k-l)!n!} \frac{k}{n-l} l. \end{aligned}$$

The last expression is equivalent to:

$$\frac{k!(n-k)!}{n!} \sum_{l=0}^{n-k} \frac{(n-l-1)!l}{(k-1)!(n-k-l)!}.$$

We will now show that this expression simplifies to (4). Consider the following:

$$\sum_{l=0}^{n-k} \frac{(n-1-l)!l}{(k-1)!(n-k-l)!} = \sum_{l=0}^{n-k} \binom{n-1-l}{k-1} l = \sum_{l=0}^{n-k} \binom{k-1+l}{k-1} (n-k-l).$$

It is, therefore, sufficient to prove that

$$\sum_{l=0}^{n-k} \binom{k-1+l}{k-1}(n-k-l) = \frac{(n-k)n!}{(k+1)!(n-k)!}.$$

We prove by induction over $n = k, k+1, \ldots$. For $n = k$, the left-hand side is 0 and so is the right-hand side. Suppose the identity is valid for some $n \geq k$, and consider the same for $n+1$:

$$\begin{aligned}
&\sum_{l=0}^{n+1-k} \binom{k-1+l}{k-1}(n+1-k-l) = \sum_{l=0}^{n-k} \binom{k-1+l}{k-1}(n+1-k-l) \\
&= \sum_{l=0}^{n-k} \binom{k-1+l}{k-1}(n-k-l) + \sum_{l=0}^{n-k} \binom{k-1+l}{k-1} = \frac{(n-k)n!}{(k+1)!(n-k)!} + \binom{n}{k} \\
&= \frac{n!}{k!(n-k)!}\left(\frac{n-k}{k+1}+1\right) = \frac{(n+1)!}{(k+1)!(n-k)!} = \frac{(n+1-k)(n+1)!}{(k+1)!(n+1-k)!}.
\end{aligned}$$

The resulting expression has the desired form. In the second line, we used the induction hypothesis and the well-known identity $\sum_{l=0}^{n-k} \binom{k+l}{k} = \binom{n+1}{k+1}$. ■

Proof of Proposition 2 Throughout this proof, we drop the asterisk in z^* for brevity. We begin by deriving the first term in (5). The coefficient on c in (3) is

$$\begin{aligned}
&\sum_{k=1}^{n} \binom{n}{k} F(z)^{n-k}[1-F(z)]^k \frac{n-k}{k+1} = \sum_{k=1}^{n} \binom{n}{k} F(z)^{n-k}[1-F(z)]^k \left(\frac{n+1}{k+1}-1\right) \\
&= \sum_{k=1}^{n} \binom{n+1}{k+1} F(z)^{n-k}[1-F(z)]^k - [1-F(z)^n] \\
&= \sum_{k=2}^{n+1} \binom{n+1}{k} F(z)^{n+1-k}[1-F(z)]^{k-1} - [1-F(z)^n] \\
&= \frac{1-F(z)^{n+1}-(n+1)F(z)^n(1-F(z))}{1-F(z)} - 1 + F(z)^n && (6) \\
&= 1 + F(z) + F(z)^2 + \ldots + F(z)^n - (n+1)F(z)^n - 1 + F(z)^n && (7) \\
&= F(z)[1 + F(z) + \ldots + F(z)^{n-1} - nF(z)^{n-1}] \\
&= F(z)\left[\frac{1-F(z)^n}{1-F(z)} - nF(z)^{n-1}\right]. && (8)
\end{aligned}$$

To obtain (6), we multiplied and divided the binomial sum by $1-F(z)$ and used the identity

$$\sum_{k=0}^{n} \binom{n}{k} F(z)^{n-k}[1-F(z)]^k = 1, \tag{9}$$

with n replaced by $n+1$. To obtain (7), we used the identity

$$\frac{1-F(z)^{n+1}}{1-F(z)} = \sum_{k=0}^{n} F(z)^k.$$

Finally, to obtain (8) we used a similar identity with $n+1$ replaced by n.

To show the existence of c_L and c_H, we transform (5). First, we write

$$\begin{aligned}
&\sum_{k=1}^{n} \binom{n}{k} F(z)^{n-k}[1-F(z)]^k \int_z^{\bar{b}} \tilde{F}_{(1:k)}(b)\mathrm{d}b \\
&= \sum_{k=1}^{n} \binom{n}{k} F(z)^{n-k}[1-F(z)]^k \int_z^{\bar{b}} [1-(1-\tilde{F}(b))^k]\mathrm{d}b \\
&= \int_z^{\bar{b}} [1-F(z)^n]\mathrm{d}b - \int_z^{\bar{b}} \sum_{k=1}^{n} \binom{n}{k} F(z)^{n-k}[1-F(b)]^k \mathrm{d}b \qquad (10) \\
&= \int_z^{\bar{b}} [1-F(z)^n]\mathrm{d}b - \int_z^{\bar{b}} [(1-F(b)+F(z))^n - F(z)^n]\mathrm{d}b. \qquad (11)
\end{aligned}$$

To obtain (10), we used (9) to write the binomial sum over $k = 1, \ldots, n$ as $1 - F(z)^n$. We also used that

$$1 - \tilde{F}(b) = \frac{1-F(b)}{1-F(z)}, \quad b \in [z, \bar{b}] \qquad (12)$$

holds for the updated distribution of benefits. Finally, to obtain (11), we used the binomial formula

$$\sum_{k=0}^{n} \binom{n}{k} [1-F(b)]^k F(z)^{n-k} = [1-F(b)+F(z)]^n. \qquad (13)$$

Second, we have

$$\sum_{k=1}^{n} \binom{n}{k} F(z)^{n-k}[1-F(z)]^k \int_z^{\bar{b}} \tilde{F}(b)\mathrm{d}b = [1-F(z)^n] \int_z^{\bar{b}} \tilde{F}(b)\mathrm{d}b.$$

Third, we integrate (1) by parts to rewrite it in the form

$$c = \bar{b} - z - \int_z^{\bar{b}} F(b)\mathrm{d}b = \int_z^{\bar{b}} [1-F(b)]\mathrm{d}b. \qquad (14)$$

Plugging these into (5), we obtain

$$\pi_{\text{WD}} - \pi_{\text{RD}} \equiv \Delta(z) = \frac{F(z)[1-F(z)^n]}{1-F(z)} \int_z^{\bar{b}} [1-F(b)]\mathrm{d}b - nF(z)^n \int_z^{\bar{b}} [1-F(b)]\mathrm{d}b$$
$$- \int_z^{\bar{b}} [1-F(z)^n]\mathrm{d}b + \int_z^{\bar{b}} [(1-F(b)+F(z))^n - F(z)^n]\mathrm{d}b + [1-F(z)^n] \int_z^{\bar{b}} \tilde{F}(b)\mathrm{d}b$$
$$= -[1-F(z)][1-F(z)^n] \int_z^{\bar{b}} [1-\tilde{F}(b)]\mathrm{d}b - nF(z)^n \int_z^{\bar{b}} [1-F(b)]\mathrm{d}b$$
$$+ \int_z^{\bar{b}} [(1-F(b)+F(z))^n - F(z)^n]\mathrm{d}b$$
$$= \int_z^{\bar{b}} [(1-F(b)+F(z))^n - F(z)^n]\mathrm{d}b - [1+(n-1)F(z)^n] \int_z^{\bar{b}} [1-F(b)]\mathrm{d}b.$$

To show the existence of c_H, note that at $c = \bar{c}$ we have $z = \underline{b}$, $F(z) = 0$, and hence

$$\Delta(\underline{b}) = \int_{\underline{b}}^{\bar{b}} [(1-F(b))^n - (1-F(b))]\mathrm{d}b < 0.$$

The existence of c_H then follows by continuity.

Finally, we show the existence of c_L. Recall that $z(c)$ is decreasing; it is, therefore, sufficient to show that $\Delta(z)$ is decreasing in z in a neighborhood of $z = \bar{b}$. Differentiating $\Delta(z)$, obtain

$$\Delta'(z) = -[1-F(z)^n - (1+(n-1)F(z)^n)(1-F(z))] \tag{15}$$
$$+ nf(z) \int_z^{\bar{b}} [(1-F(b)+F(z))^{n-1} - F(z)^{n-1} - (n-1)F(z)^{n-1}(1-F(b)]\mathrm{d}b.$$

The first term in (15) can be further transformed as

$$-[1-F(z)] \left[\sum_{k=0}^{n-1} F(z)^k - 1 - (n-1)F(z)^n \right] = -[1-F(z)] \sum_{k=1}^{n-1} [F(z)^k - F(z)^n]$$
$$= -[1-F(z)] \sum_{k=1}^{n-1} F(z)^k [1-F(z)^{n-k}] = -[1-F(z)]^2 \sum_{k=1}^{n-1} F(z)^k \sum_{l=0}^{n-k-1} F(z)^l. \tag{16}$$

The second term in (15) can be transformed as

$$
\begin{aligned}
& nf(z)\int_z^{\bar{b}}[1-F(b)]\left[\sum_{k=0}^{n-2}(1-F(b)+F(z))^{n-2-k}F(z)^k-(n-1)F(z)^{n-1}\right]\mathrm{d}b \\
&= nf(z)\int_z^{\bar{b}}[1-F(b)]\sum_{k=0}^{n-2}F(z)^k\left[(1-F(b)+F(z))^{n-2-k}-F(z)^{n-1-k}\right]\mathrm{d}b \qquad (17)\\
&= nf(z)\int_z^{\bar{b}}[1-F(b)]\sum_{k=0}^{n-2}F(z)^k\left[\sum_{l=1}^{n-2-k}\binom{n-2-k}{l}(1-F(b))^l F(z)^{n-2-k-l}\right.\\
&\left.+F(z)^{n-2-k}-F(z)^{n-1-k}\right]\mathrm{d}b \qquad (18)\\
&= nf(z)[1-F(z)]^2\int_z^{\bar{b}}[1-\tilde{F}(b)]\left[\sum_{l=1}^{n-2-k}\binom{n-2-k}{l}(1-\tilde{F}(b))(1-F(b))^{l-1}F(z)^{n-2-k-l}\right.\\
&\left.+F(z)^{n-2-k}\right]\mathrm{d}b. \qquad (19)
\end{aligned}
$$

To obtain (17), we represented $(n-1)F(z)^{n-1}$ as $\sum_{k=0}^{n-2}F(z)^{n-1}$ to bring $F(z)^{n-1}$ inside the common sum and then extracted the multiplier $F(z)^k$. For (18), we used the binomial representation similar to (13). Finally, for (19), we used (12).

Combining (16) and (19), we can write (15) as

$$\Delta'(z) = -[1-F(z)]^2\left[\sum_{k=1}^{n-1}F(z)^k\sum_{l=0}^{n-k-1}F(z)^l - S(z)\right],$$

where $S(z)$ is the term multiplying $[1-F(z)]^2$ in (19). Importantly, $S(z)$ converges to zero for $z \to \bar{b}$, whereas the double sum in brackets converges to a positive number; therefore, there exists a $z_0 < \bar{b}$ such that $\Delta'(z) < 0$ for all $z \in (z_0, \bar{b})$, which implies the existence of c_L. ■

B Belief updating

As mentioned in Section 2, throughout the paper we assume that buyers are boundedly rational in that they do not update their beliefs about the underlying distribution of values having observed the default option. In this section, we explore the consequences of such updating in more detail. While in general the answer depends on the shape of the distribution of values, for a large class of distributions, including the one used in our experiment, the consequences are minimal and confined to the cases where none of the n options are above the cutoff $z^*(c)$ (see footnote 8).

We note first that if a buyer observes a default with value below $z^*(c)$, she can conclude that all n options have benefits below $z^*(c)$ and refrain from further search. This would not be an equilibrium outcome if the seller were strategic; however, it is the buyer's optimal response in our experiment where sellers are automated.

Consider now a setting where a buyer observes a default option such that $b_1 > z^*(c)$. She can then conclude that there are no options with values in the interval $[z^*, b_1]$, and hence her updated distribution of values becomes

$$\hat{F}(b; c, b_1) = \frac{1}{1 - F(b_1) + F(z^*)} \begin{cases} F(b), & b \in [\underline{b}, z^*] \\ F(z^*), & b \in [z^*, b_1] \\ F(b) - F(b_1) + F(z^*), & b \in [b_1, \bar{b}] \end{cases} \tag{20}$$

This updated distribution produces a modified optimal cutoff $\hat{z}(c, b_1)$ that is, in general, different from $z^*(c)$, and depends on the observed realization of optimal default. Our main interest is in whether it is possible to have $\hat{z}(c, b_1) > b_1$, i.e., whether the belief updating can lead to additional search. The answer is negative in a wide range of cases, as stated in the following proposition.

Proposition 3 *Suppose the distribution of benefits F has an increasing hazard rate. Then $\hat{z}(c, b_1) \leq b_1$.*

Proof Assume, by contradiction, that $\hat{z} > b_1$. Using representation (14) for the optimal cutoff, we obtain that $\hat{z}$ must satisfy

$$\int_{\hat{z}}^{\bar{b}} [1 - \hat{F}(b; c, b_1)] \mathrm{d}b = c.$$

Equation (20) then gives

$$\int_{\hat{z}}^{\bar{b}} \left[1 - \frac{F(b) - F(b_1) + F(z^*)}{1 - F(b_1) + F(z^*)}\right] \mathrm{d}b = c,$$

which, using (14) to represent c, can be written as

$$\int_{\hat{z}}^{\bar{b}} [1 - F(b)] \mathrm{d}b = [1 - F(b_1) + F(z^*)] \int_{z^*}^{\bar{b}} [1 - F(b)] \mathrm{d}b. \tag{21}$$

The integral in the left-hand side of (21) is decreasing in $\hat{z}$ and equals zero for $\hat{z} = \bar{b}$. A necessary and sufficient condition for (21) to have a solution $\hat{z} > b_1$ is, therefore,

$$\int_{b_1}^{\bar{b}} [1 - F(b)] \mathrm{d}b > [1 - F(b_1) + F(z^*)] \int_{z^*}^{\bar{b}} [1 - F(b)] \mathrm{d}b. \tag{22}$$

We will now show that the opposite inequality holds. Splitting the integral in the right-hand side,

$$\int_{z^*}^{\bar{b}} [1 - F(b)] \mathrm{d}b = \int_{z^*}^{b_1} [1 - F(b)] \mathrm{d}b + \int_{b_1}^{\bar{b}} [1 - F(b)] \mathrm{d}b,$$

we further rewrite (22) as

$$[F(b_1) - F(z^*)] \int_{b_1}^{\bar{b}} [1 - F(b)] \mathrm{d}b > [1 - F(b_1) + F(z^*)] \int_{z^*}^{b_1} [1 - F(b)] \mathrm{d}b. \tag{23}$$

We can show, however, that

$$[F(b_1) - F(z^*)] \int_{b_1}^{\bar{b}} [1 - F(b)] \mathrm{d}b \leq [1 - F(b_1)] \int_{z^*}^{b_1} [1 - F(b)] \mathrm{d}b, \tag{24}$$

which contradicts (23). Rewrite (24) as

$$\int_{z^*}^{b_1} f(x) \mathrm{d}x \int_{b_1}^{\bar{b}} [1 - F(y)] \mathrm{d}y \leq \int_{b_1}^{\bar{b}} f(y) \mathrm{d}y \int_{z^*}^{b_1} [1 - F(x)] \mathrm{d}x,$$

or, equivalently,

$$\int_{z^*}^{b_1} \left[\int_{b_1}^{\bar{b}} [f(x)(1 - F(y)) - f(y)(1 - F(x))] \, \mathrm{d}y \right] \mathrm{d}x \leq 0. \tag{25}$$

Note that $x \leq y$ in the domain of integration. The increasing hazard rate property then implies

$$\frac{f(x)}{1 - F(x)} \leq \frac{f(y)}{1 - F(y)},$$

which implies the integrand in (25) is negative, and hence the inequality holds. ∎

The class of increasing hazard rate distributions (also known in the reliability theory as *increasing failure rate*, or IFR) includes many standard distributions such as the uniform, normal, exponential, logistic, or Gumbel. Any log-concave distribution is IFR (but not the other way around). The IFR property is associated with sub-exponential (or *light*) tails. In contrast, distributions violating the IFR property are *heavy-tailed* distributions such as the Pareto (power laws) family.

Intuitively, heavy-tailed distributions are relatively more likely to produce large realizations away from the mean. In our context, this implies the updated distribution may have a larger weight shifted to the upper tail $[b_1, \bar{b}]$, and hence a buyer may expect sufficient benefits to justify additional search.

We conclude that in our experiment, where the distribution of benefits is uniform, belief updating would not affect subjects' search behavior except in rare cases when the buyer's acceptance set is empty.

C Defaults with fixed sample size search

In this section, we analyze the effect of the optimal default characterized in Proposition 1 when the buyer's search is nonsequential. As we show, the effect of default is qualitatively very similar to the case of sequential search, and hence our predictions are to a certain extent robust to assumptions about search.

Specifically, we consider a fixed sample size search algorithm where, having observed a default option with benefit b_1, the buyer chooses a sample size $s \in \{0, \dots, n-1\}$, randomly draws s other options, at cost cs, and selects the option with the largest benefit among the $s+1$ options (including the default).

Conditional on b_1, the buyer's expected payoff from sampling s other options is

$$\pi_s(b_1) = \mathbb{E}(\max\{b_1, b_{(s:s)}\}|b_1) - cs = b_1 F(b_1)^s + \int_{b_1}^{\bar{b}} b\mathrm{d}F(b)^s - cs. \tag{26}$$

For $s \geq 1$, let $\Delta\pi_s(b_1) = \pi_s(b_1) - \pi_{s-1}(b_1)$ denote the payoff's first difference with respect to s. Integrating (26) by parts, we can write it as

$$\Delta\pi_s(b_1) = \int_{b_1}^{\bar{b}} F(b)^{s-1}[1 - F(b)]\mathrm{d}b - c. \tag{27}$$

As seen from (27), $\Delta\pi_s(b_1)$ is decreasing in s, implying that $\pi_s(b_1)$ is discrete concave in s. Additionally, $\Delta\pi_s(b_1)$ is decreasing in b_1 and in c, and hence, from the monotone comparative statics, so does $\arg\max_s \pi_s(b_1)$. The payoff-maximizing choice of s is, therefore, characterized as follows.

Proposition 4 *(i) There exists a generically unique optimal sample size*

$$s^*(b_1) = \begin{cases} 0, & \text{if } \Delta\pi_1(b_1) < 0 \\ \max\{s \in \{1, \dots, n-1\} : \Delta\pi_s(b_1) \geq 0\}, & \text{otherwise} \end{cases}$$

(ii) $s^*(b_1)$ is decreasing in b_1 and in c.
(iii) $s^*(b_1) = 0$ for $b_1 > z^*$.

To verify part (iii), it is easy to show via integration by parts that $\Delta\pi_1(z^*) = 0$, where z^* is the solution of (1).

In the baseline setting where the default is random, the buyer's *ex ante* expected payoff is simply $\pi_{\text{RD}} = \int \pi_{s^*(b)}(b)dF(b)$. When the default is chosen optimally as in Proposition 1, almost surely either (i) $b_{(n:n)} < z^*$, i.e., all the realized benefits are below the reservation value, and the default is chosen randomly; or (ii) $b_{(n:n)} > z^*$, in which case a default $b_1 > z^*$ is chosen, and hence, from part (iii) of Proposition 4, the optimal number of searches is zero as in the sequential search case. The buyer's expected payoff is then

$$\begin{aligned} \pi_{\text{WD}} = F(z^*)^n \int_{\underline{b}}^{z^*} \left[b\underset{\sim}{F}(b)^{s^*(b)} + \int_b^z b'\mathrm{d}\underset{\sim}{F}(b')^{s^*(b)} - cs^*(b) \right] \mathrm{d}\underset{\sim}{F}(b) \\ + \sum_{k=1}^{n} \binom{n}{k} F(z^*)^{n-k}[1 - F(z^*)]^k \int_{z^*}^{\bar{b}} b\mathrm{d}\tilde{F}_{(1:k)}(b). \end{aligned} \tag{28}$$

Here, $\underset{\sim}{F}(b) = \frac{F(b)}{F(z^*)}$ is the conditional distribution of benefits below the reservation value. The first term represents the expected payoff from fixed sample size search when all options are below z^* (the probability of this event is $F(z^*)^n$), and the default is chosen randomly from $\underset{\sim}{F}$. However, the buyer is unaware of that and still selects the sample size according to the rule in part (i) of Proposition 4. The second term, similar to (2), sums up over all possible numbers of options, k, with benefits above z^*, for each of which $\tilde{b}_{(1:k)}$—the lowest order statistic from the updated distribution $\tilde{F}(b) = \frac{F(b)}{1-F(z^*)}$—is set as the optimal default.

As seen from (28), the same two effects are at play here as in the case of sequential search. When the cost of search is low, the optimal default is high, and the buyer benefits from it due to savings on search costs. That benefit, however, is small because as soon as the search cost rises enough for the probability of having more than one option above z^* to become nontrivial, those savings are outweighed by losses from the unavailability of the best options. As the cost of search approaches $\bar{c}$, the buyer does not search and the optimal default is set at the worst possible option, implying $\pi_{\text{WD}} < \pi_{\text{RD}}$. By continuity, a c_H similar to the one identified in Proposition 2 then exists as well.

D Experimental instructions (Low Cost with Announcement)

Welcome and thank you for participating in todays experiment. Please turn off your phone now and put it away. Please do not talk during the experiment. **If you have a question, please type it in the Zoom chatbox and send it only to the experimenter who will answer it**.

Your earnings in this experiment will depend on your own choices and on chance moves. Understanding the instructions is likely to increase your earnings. Earnings are private. You will receive a $5.00 participation fee. You will be asked to submit your PayID at the end of the experiment to receive the online transfer of your earnings.

The Choice Tasks and Payoffs: There are **80 decision rounds** in this experiment.

In each round, you will collect points depending on your choice and on chance. At the end of the experiment, <u>4 of the 80 rounds</u> will be chosen randomly and the points you earn in those rounds will be paid out to you with an exchange rate of $1 for every 100 points.

<u>**Endowment**</u>

At the beginning of each round, you will receive an endowment of 200 points.

<u>**Offers**</u>

For each round, the values for **10** offer cards were randomly generated by the computer.

All values are integers between and including 0 and 100. Each of these values is equally likely, and independent of others. These values differ from round to round

One of the offer cards is always chosen as the initial offer. The 9 remaining cards are reshuffled and placed in a random order every round. The initial offer card is always shown on the top.

If you like the initial offer, you can accept it immediately.

If you do not like the initial offer, you can reveal further offers.

How the initial offer is determined[15]

In 50% of rounds, selected randomly, the initial offer is random just like the remaining 9 (hidden) offers.

In the other 50% of rounds, the initial offer is carefully chosen from among the 10 random offers by a profit-maximizing seller. The seller's profit is negatively related to the value of the offer that you eventually accept. **The seller has selected the lowest offer that it believes you will accept without searching**.

Cost of revealing other offers

Revealing additional offers incurs a fixed cost of 5 per offer.

So your COST in a round equals (number of offers you reveal) $\times$ 5 cents

Accepting an offer and the round termination

You can always accept the best offer revealed so far. Accepting an offer terminates the round.

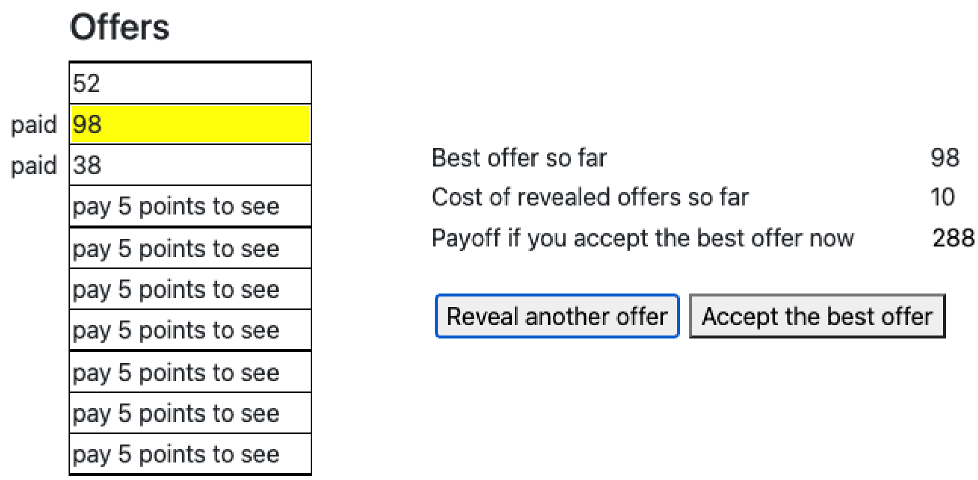
Your Payoffs

Your payoff in a round equals:

200 + BEST OFFER at the moment you accept − YOUR COST in that round

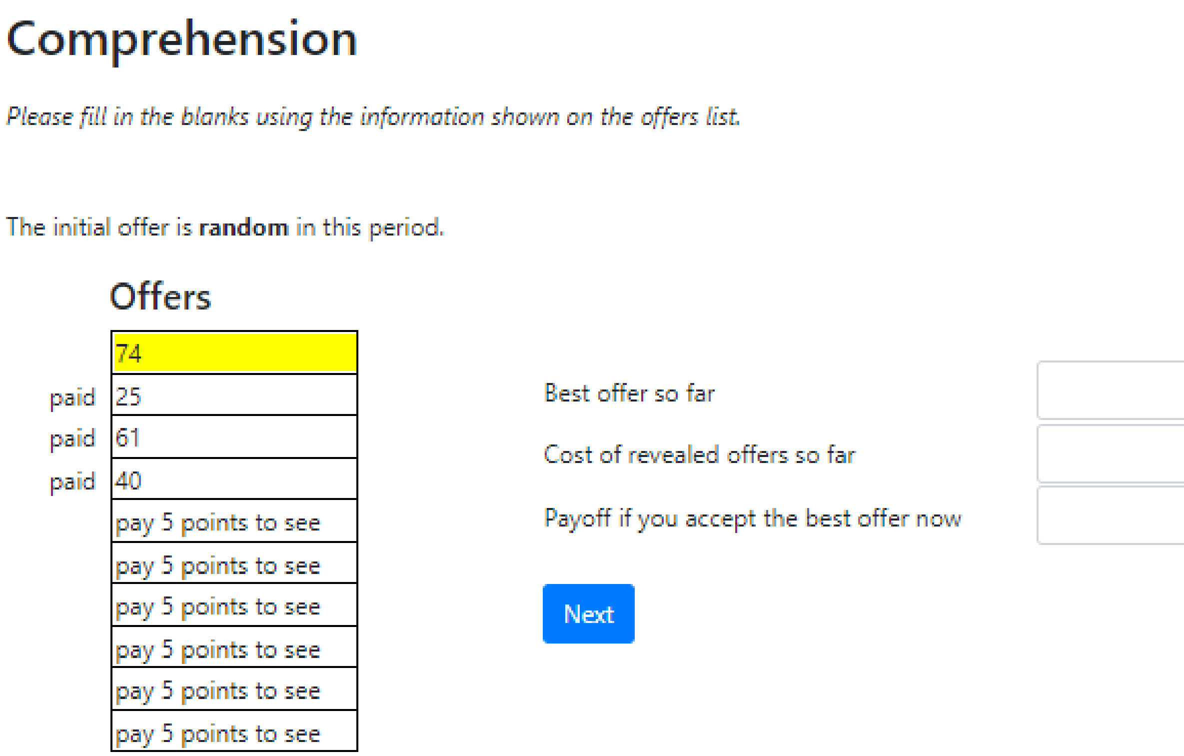
In this experiment you will get information about the best offer so far, about the cost of the offers so far and about what your payoff would be if you accepted at that moment. Here is an example:

[15] This section is absent in the treatments without announcement.



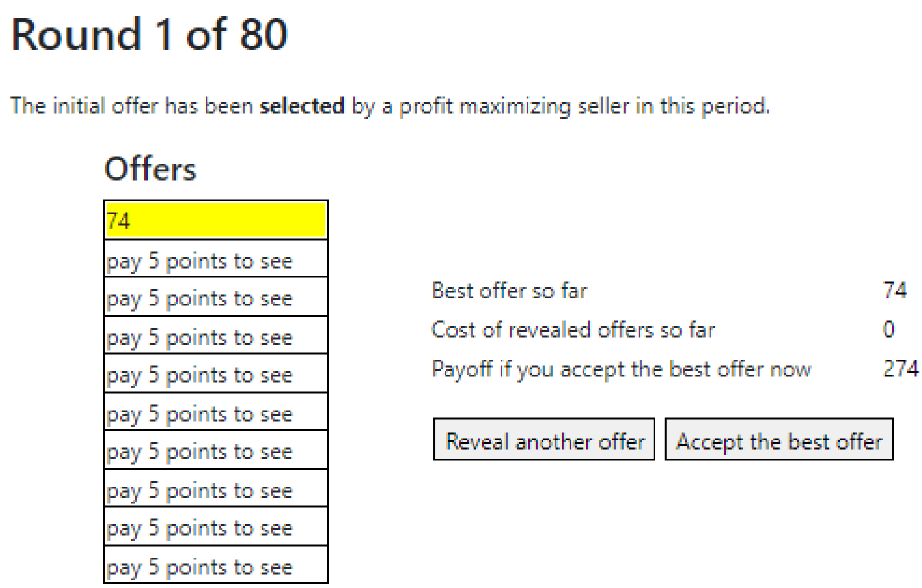
If you have any questions at this time, please message one of the experimenters using the chat function in Zoom. If there are no questions, please go ahead and complete a quiz.

Note that the instructions will remain on your screen for future reference.



Actual decision screens (a WD round with announcement)

(a) The beginning of a round



(b) After 3 searches