Choosing to search: Choice with a default option*

Ian Chadd[†], Emel Filiz-Ozbay[‡], Erkut Y. Ozbay[§]

May 12, 2023

Abstract

In the presence of a default option, the optimal search rule for an agent with a reference-dependent utility and a search cost predicts: (i) the default increases the reservation utility due to the *reference effect*, leading to a better choice, and (ii) those with higher reservation utility will *self-select* into search and are more likely to find a superior option. Our experiments document the presence of both effects. Those who reject the default are likely to find higher-ranked options in their active search, supporting the self-selection effect. Even when the self-selection channel is shut down, the reference effect remains.

JEL Codes: C91, D83, D91
Keywords: Default option, Endogenous choice, Reference dependence.

*We would like to thank Pietro Ortoleva and Daniel Martin for their comments and feedback. We also thank for the feedback we received from the participants of ESA-World Meetings, D-TEA conference, and Sydney Experimental and Behavioral Research Group Seminar Series. The experiments were funded by NSF DDRIG, Grant Award ID 1757253.

[†]Department of Economics, Rensselaer Polytechnic Institute, Email: chaddi@rpi.edu
[‡]Department of Economics, University of Maryland, Email: efozbay@umd.edu
[§]Department of Economics, University of Maryland, Email: ozbay@umd.edu

1 Introduction

Information acquisition is fundamental in making good decisions. However, in a broad class of economically relevant search problems, an individual incurs a cost to evaluate alternatives[1] and may then fail to consider all available options, leading to them missing out on better options (e.g. Gabaix et al., 2006; Caplin et al., 2011). Furthermore, in the presence of a *default* option, individuals have a tendency to stick with this default.[2] While sticking with the default option is an easy way of making a choice, still some individuals opt out of their defaults, exert effort to evaluate their non-default options, and make an *active choice*.[3] Hence, in order to assess the merits of default options, it is crucial to investigate the channels by which a default option may influence the active choice.

As an example consider a conference participant who attends meetings in an unfamiliar city and needs to decide what to eat for lunch. By incurring a cost, which may be imposed by the time or cognitive capacity allocated, she can search for other lunch options in the area. Suppose a sandwich is provided by the conference organizers and it is her default option. The presence of such a default option, firstly, may switch on a "reference-dependence" channel in her choice and she may evaluate the other available options with respect to this default if she chooses to search other restaurants actively. Although standard models assume that individuals should evaluate alternatives independent of the default option, consuming alternatives better or worse than the reference may trigger a sense of gain or loss in the sense of Kahneman and Tversky (1979).[4] Secondly, the offer of a default option may activate

[1]For example, when choosing a retirement savings plan, one needs to read the plan details and create a portfolio. Moreover, individuals are conceivably heterogeneous in their costs, for example, in a retirement savings decision, evaluation requires financial literacy and evaluating alternatives is less costly for the financially literate individuals.

[2]E.g. retirement saving (Madrian and Shea, 2001), prescription drug insurance (Ericson, 2014), consumer product configuration (Levav et al., 2010).

[3]We follow the "active choice" terminology of Chetty et al. (2014) to distinguish between settling with a default option versus evaluating and choosing from the available set of other options. The latter behavior is called "active choice" throughout the paper.

[4]Reference-dependence has been robustly shown in various contexts (for a detailed review see

the "self-selection" channel: Only those whose expected net benefit of searching other options exceeds the value of the default will "self-select" into active search. This rational channel is present even under the standard model, and it operates similar to the entry decision in endogenous entry games such as auctions or tournaments where individuals with higher expectations from the game than the entry cost enter the game (e.g. Levin and Smith, 1994; Bajari and Hortaçsu, 2003; Boosey et al., 2020) or voting for game change for those whose expected payoff from the new game exceeds the status-quo game (Bo et al., 2010). So, in the above example of lunch choice at a conference, according to the reference-dependence channel, the participant will feel a loss if she ends up with a lunch option inferior to the default sandwich option that she didn't choose. Similarly, finding an option superior to the default may create an additional gain feeling. Hence, she may search more in order to avoid loss or to increase gain. According to the self-selection channel, only the participants who believe that they can find a superior lunch option than the sandwich will incur the search cost and look for an alternative restaurant in the area.

In this paper, we study a theoretical model of an optimal search problem of an agent with reference-dependent utility (gain/loss utility) and a search cost in the presence of a default option. We conduct experiments to test the theoretical predictions regarding the reference and self-selection effects introduced by the default. In the experiments, our subjects select among options that are presented as sequences of symbols of # and %. The monetary value of an option is equal to the number of # symbols in the sequence.[5] Note that in such a choice task, understanding the monetary value of an option requires effort and hence it corresponds to the costly

O'Donoghue and Sprenger, 2018). Furthermore, it has been shown that a reference-dependent model fits the data better than the standard model, e.g. job search (DellaVigna et al., 2017), retirement age decision (Seibold, 2021). Reference dependent utilities are also applied various environments under uncertainty à la Kőszegi and Rabin (2006) such as evaluation of experiences (Bushong and Gagnon-Bartsch, 2022; Gagnon-Bartsch and Bushong, 2022) and social comparisons (Langtry, 2022).

[5]In similar option choice experiments, Caplin et al. (2011) and Chadd et al. (2021) present the value of each option as a sequence of addition and subtraction operations. In order to avoid the possibility of cheating in an online platform, we use a different task.

search problem we study theoretically.

To identify the marginal impact of the reference and self-selection effects, we first note that while the reference-dependence channel is always active whenever there is an option serving as a reference, the self-selection channel is present only if an individual voluntarily opts-out of the default option. Hence, the opt-out decision being voluntary (endogenous) or not is key for the self-selection effect. To isolate the two effects, we introduce a treatment where everyone knows about the default but subjects are sometimes forced to opt out of the default option.[6] We call this the Exogenous Treatment since the subjects are forced exogenously to search through other options actively after seeing the default. This is an advantage of collecting data in a controlled experiment.[7]

Comparing the active choices when the default option is involuntarily opted out and when there is no default option identifies the impact of the reference-dependence channel; comparing the active choices in the presence of a default option when it is voluntarily and involuntarily opted out yields the additional impact of the self-selection channel. To be able to make all these comparisons, our experiment consists of three treatments: In the Baseline Treatment, there is no default option, all the alternatives are shown to the subjects, the subjects need to examine an alternative to determine its value, and they have to choose actively. We have two treatments with a reference option. In the Exogenous Treatment, first the value of the default option is presented, and then each subject is randomly (with equal probability) given either the default option or forced to actively choose from the set of alternatives as in the Baseline Treatment. In the Endogenous Treatment, we offer subjects a default

[6]This is similar to the exogenous versus voluntary game change implemented by Bo et al. (2010) in a multi-player voting game to isolate and control for the selection effect. Selection has a more direct effect in our setting as we do not have the strategic interaction and belief formation aspects of Bo et al. (2010) in our single-person decision problems.

[7]The Exogenous Treatment not only enables us to turn on the reference channel without the self-selection possibility, but also resembles some applications where individuals are aware of a default option which they are not allowed to choose. For example, an option that was previously consumed or recommended by a friend could be the reference option that is unavailable to the decision maker at the time of choice, or she may be ineligible for that option.

option and each subject either voluntarily picks this option or actively chooses from the set of alternatives as in the Baseline Treatment. The comparison between the Baseline and Exogenous Treatments will capture the reference-dependence channel, and the comparison between the Exogenous and Endogenous Treatments will capture the self-selection channel.

We build our testable hypotheses based on the theoretical predictions for the choice problems in each treatment. We investigate an optimal search model under reference-dependent utility via the gain/loss utility model where the value of the default option serves as the reference point. We use the functional form of Kőszegi and Rabin (2006) which is built on the prospect theory of Kahneman and Tversky (1979) and simplify it by ruling out diminishing sensitivity and probability weighting. In the current model, a decision maker holds a belief in the distribution of option values and incurs a cost to learn the value of each alternative. So, at each point of the search, she evaluates whether the reference-dependent utility of continuing the search exceeds the cost of it. The optimal strategy is a cutoff rule characterized by a reservation utility: stop searching once an option with a value higher than the reservation utility is found (Result 1), otherwise keep searching.

Our theoretical comparative statics imply that the reservation utility is higher when there is a reference. In other words, more search is expected in the presence of a default option, and hence, the quality of active choices in the Exogenous Treatment will be better than in the Baseline Treatment. Additionally, an individual with a lower search cost has a higher reservation utility, implying that she searches more. These theoretical results have some immediate implications for the experiments. For example, there is a cutoff search cost such that only those whose costs are below the cutoff would reject the default option and self-select into an active choice in the Endogenous Treatment.[8] Hence, the quality of active choices in the Endogenous Treatment will be superior than the one in the Exogenous one.[9]

[8] A similar result can be derived based on gain/loss parameters as well.

[9] This is consistent with the findings of (Chetty et al., 2014) who show that more financially

Our design allows us to address several problems present in the field data. Despite substantial research on default options in numerous environments, several obstacles in field data prevent the joint study of the impacts of the reference-dependence and self-selection channels on the quality of the active choice. First, due to subjective valuations of the alternatives in applications (such as insurance or retirement plan choices), it is not possible to determine the quality of active choices without making additional assumptions. To overcome this obstacle, we design experiments where the subjects' choice is on objectively valued options, hence any change in choice due to the presence of a default can be measured in terms of the change in the objective value of the chosen alternative.

Secondly, identifying the marginal contributions of reference and self-selection effects of default option might not be possible with field data. Note that, in those environments, when there is no default option, none of these effects are present, but when the default is offered and the individuals decide whether to opt out of the default option, both effects are activated.

Our results have direct policy implications for choice architects. Providing some reference to consumers in the form of default option may overall lead to superior choices. The gain/loss motivation caused by a reference would incentivize any type of consumer to search more. Moreover, the availability of a default helps consumers with poor searching skills (or high searching costs) to settle for a choice with higher value without exerting search effort than what they expect to find if they have searched actively.

The rest of the paper is organized as follows. Sections 2 explains the design of the experiments. Section 3 provides a theoretical model of search with reference dependent utility and characterizes the optimal search rule. Section 4 reports the data analysis of the experiments. Section 5 concludes with a discussion of our findings and their implications. The proofs are in Appendix A. Experimental instructions with

sophisticated individuals tend to opt out of the default contributions and actively choose their contributions to retirement savings.

screenshots can be found in Appendix B.

2 Experimental Design

The experiments were programmed in oTree (Chen et al., 2016) and the data was collected online via the Prolific platform in Fall 2020. Each subject participated in the experiment only once.

When a session started, a subject first approved an online consent form and received the instructions for the relevant treatment.[10] Next, 20 decision problems appeared one by one. Each subject, across all treatments, saw the same set of decision problems, the order of which were randomized at the subject level. We used Experimental Currency Units (ECU) in the experiments with an exchange rate of 10 ECU=$1. At the end of the experiment, subjects were paid for one randomly selected decision that they made. On average, subjects earned $3.58, including the participation fee of $1, for an average of approximately 15 minutes of participation.

A choice problem was presented as a choice list with 10 options in it. Figure 1 shows an example of a choice problem. Each option was displayed as a sequence of 50 symbols constructed by % and #. The value of an option is the number of # symbols in the sequence. Therefore, the optimal choice would be to select the option with the highest number of # symbols. In order to make the decision more challenging, only the option that the subject's cursor is on is highlighted (it is Option 2 in Figure 1.) Hence, the subject needs to move the cursor around in order to evaluate each option.[11] The subjects were given 120 seconds to make a selection and submit it by clicking a submission button on the screen. If they failed to submit an option within

[10] See Appendix B for screenshots of the instructions.

[11] Because the experiment was run online with less experimenter monitoring than is available in a lab experiment, a natural concern is that subjects might "cheat" somehow in order to maximize their earnings with little effort. In order to prevent an obvious form of cheating, options in each decision problem were presented using a picture (png file) rather than text. This way subjects could not simply copy and paste the decision problem to another piece of software (e.g. Microsoft Excel or Word) to count the # symbols for them.

this time limit, they got a payoff of zero ECU for that problem.

In order to generate option values, for each decision problem we randomly drew 10 values from a normal distribution with a mean of 20 ECU and a standard deviation of 8 ECU. We repeated this process, redrawing from the same distribution, until each decision problem had i) a unique option with maximal value and ii) no options with value less than 0 ECU.

We have three treatments such that all of the treatments are identical in terms of the available 20 decision problems. They differ based on the existence of a default option and, in the case of default option, they differ by whether this option can be endogenously chosen by the subject or exogenously assigned to the subject.

Baseline Treatment: In this treatment, a subject sees all the options in a choice problem without any default or reference option. For each problem, she makes a choice from the presented list of options, submits her choice, and moves to the next problem. She responds to 20 choice problems in total. No default option is presented.

Endogenous Treatment: In this treatment, for each problem, a subject is first *offered* a default option of 14ECU. If she takes this offer, she moves on to the next problem without having to choose between the 10 options. If she rejects this offer, she sees the 10 options similar to the Baseline. This procedure repeats for each of the 20 decision problems presented in a session.

Exogenous Treatment: In this treatment, for each problem, a subject is first *presented* a default option of 14ECU. She is told that with 50% chance she will receive this amount for the current problem and with 50% chance she will see a choice problem with 10 options on the next screen. If the latter event occurs, she makes an active choice similar to the other two treatments. For each of the 20 decision problems in the session, there is an independent randomization for getting the default

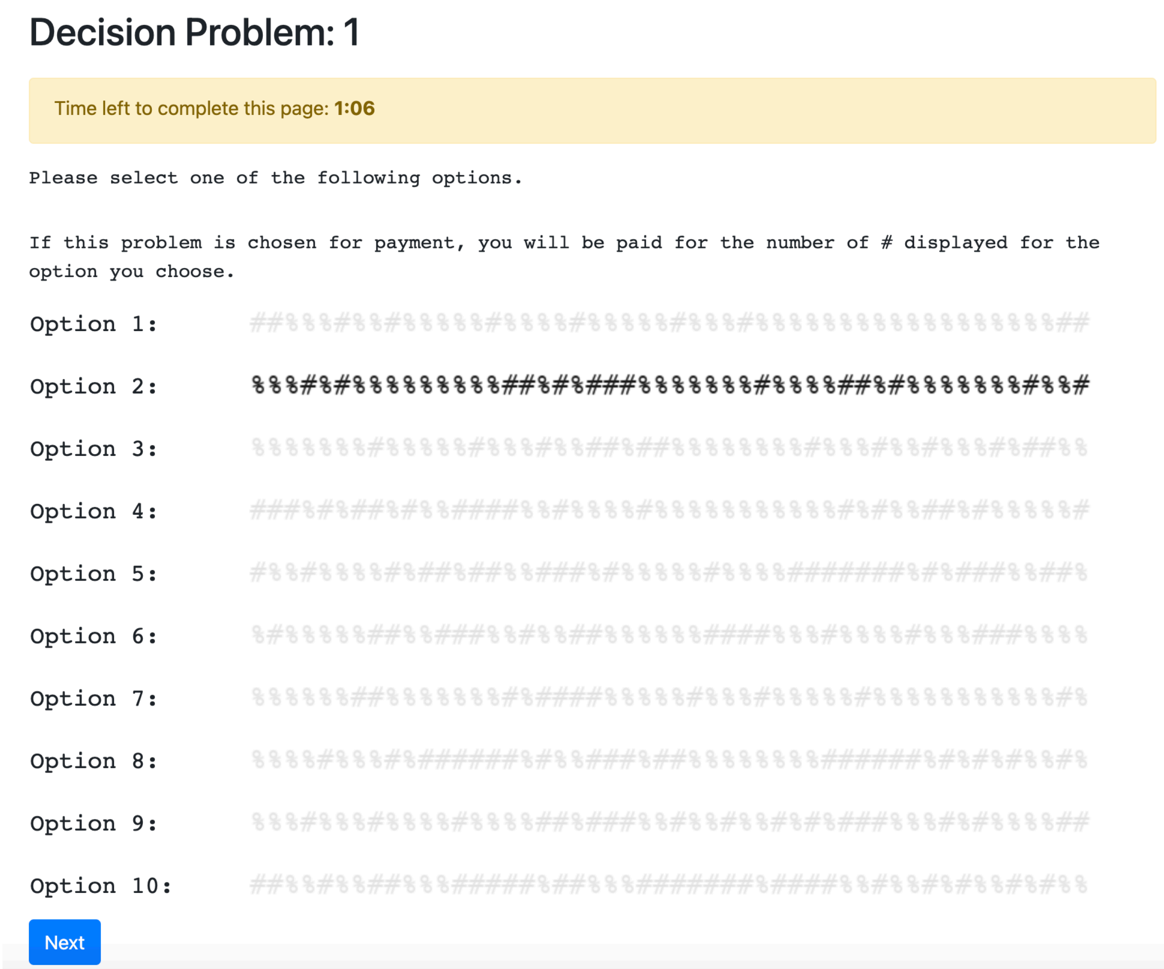


Figure 1: An example decision screen

Notes: The above screenshot displays an example decision problem. Option sequences were partially hidden unless the cursor hovered over the option, as is the case for Option 2 in the above. The value of an option was the number of # symbols in the sequence. Option 2 was therefore worth 14 ECU ($1.40) if it was chosen by a subject in a given decision problem. Subjects were not paid for the decision problem if they did not i) select an option in the list (by clicking it) or ii) click the Next button before the time allotted (highlighted at the top of the screen) ran out.

option or making an active choice for that problem.

We chose 14 ECU as the value of the default option in the Exogenous and Endogenous treatments since it was lower than the mean so that we would have meaningful self-selection, but not so low[12] that no subjects would ever choose the default option. Section 4 presents evidence that this was effective.

In our Endogenous Treatment, if a subject rejects a default and starts active search, the default is no longer available to her. Note that otherwise it is hard to deduce whether active search is conducted or not for a subject choosing the default since it can happen either because the subject did not like any other option or because she did not consider anything else. In such an environment, the underlying consideration model needs to be known in order to identify the likelihood of an active choice (Abaluck and Adams-Prassl, 2021). In an experiment, this complication may be trivially eliminated entirely by excluding the rejected default from the active search, so that the choice of default directly reveals that the active search is not performed.[13]

We collected decisions from 70, 99, and 157 participants in the Baseline, Endogenous, and Exogenous Treatments, respectively. There are more subjects in the Endogenous Treatment than in the Baseline to have enough observations of active choice in the former. The number of subjects is the highest in the Exogenous Treatment because only half of all observations were of active choice by design. Additionally, we filter out inattentive subjects by excluding those who spent very little time (less than 15 seconds) on the initial instructions page. We also exclude

[12] 14 ECU is less than one standard deviation lower than the mean.

[13] The rejected default being removed from the set of available options in an active search is also relevant for some applications. For example, if the default has limited availability then when it is rejected by an agent, it will be taken by someone else, or the default option may be offered as a take-it-or-leave-it offer. There may also be legal reasons for unavailability of the default once rejected. For example, a college athlete needs to resign from her existing team in order to initiate an active search. Opting out of the default option may be costly as in Carroll et al. (2009), and if this cost is high enough, it may even nullify the benefit of the default option once it is rejected.

Table 1: Treatment Summary

	Treatment		
	Baseline	Endogenous	Exogenous
Default Option	✗	✓	✓
Selection	-	✓	✗
Channels	-	Reference Self-Selection	Reference
N	70	99	157
Attentive N	65	92	147

Notes:
"Default Option" indicates whether there was a 14 ECU default option presented to the subject. "Selection" indicates whether the subject could select the default option endogenously. "Attentive" indicates that the subject spent more than 15 seconds on the initial instructions page and never timed out.

subjects who failed to choose an available option within the allotted time in at least one decision problem where they had to make an active choice. These two exclusions of inattentive subjects led to dropping approximately 5% of our subjects across each treatment. This results in 65, 92, and 147 attentive subjects in the Baseline, Endogenous, and Exogenous Treatments, respectively. This and other relevant treatment details are summarized in Table 1.

3 Model of Optimal Search with a Default Option

In order to form our hypotheses, we investigate an optimal search model allowing a reference-dependent utility, and we derive the optimal search strategy that applies to our three treatments. The proofs are in the Appendix.

In particular, we employ a reference-dependent utility function based on Kőszegi and Rabin (2006) which builds on the prospect theory model of Kahneman and Tversky (1979), and for simplicity assume away diminishing sensitivity and probability weighting: $u(x, r) = x - \beta(r - x)^+ + \gamma(x - r)^+$, where $x \in \mathbb{R}_+$ is the value of an option, $r \in \mathbb{R}_+$ is a reference, and $(y)^+ := max\{y, 0\}$. Note that in this specification, in addition to the consumption utility denoted by the first term, there is disutility from having an option with a value lower than the reference as well as additional gain when consumption exceeds the reference. The coefficients $\beta \geq \gamma \geq 0$ are the loss and gain parameters, respectively.

We treat the default option as the static reference when it is present. This is natural for our experiment where the decision is relatively quick and the default is not available once the active search starts; hence, a subject may compare the options that she finds out through search with respect to the forgone reference of the default. The literature specifies different references depending on the context. DellaVigna et al. (2017) takes the average income of previous rounds in a job search problem. Job search for an unemployed worker is a long process and previous income affects standards of living. Hence, a person may compare searched options with respect to those standards. This aspect doesn't exist in our search setting, so we shut down the evolving reference channel, as it is not central to our research question of selection versus reference effects. Backward-looking references have also been used by Bowman et al. (1999) in the context of consumption and savings problems.

In our setup, there are a number of alternatives and the value of each alternative is unknown to the decision maker, but she knows that the values are distributed i.i.d. by $F(x)$. The value of an alternative can be learned by incurring a cost. Let $c > 0$ denote the cognitive cost of searching one more option. We assume that c is less than the expected value of the option given F so that search might be meaningful at least for some situations, i.e. $E[x] > c$. The person may learn each option sequentially in any order she wants. The decision maker has the option of earning zero by not doing anything for the duration of the experiment: this is what we paid to subjects if they do not make any decision in 120 seconds. We define the decision problem in discrete time where in each period $t \in \{0, 1, ..., T\}$, the decision maker decides whether to evaluate an option or not. At $t = 0$, not searching means taking the default in the

Endogenous Treatment, and it means receiving zero in the other two treatments. When search is stopped in a given period, the decision maker selects the alternative with the highest reward among the ones of which she has learnt their values so far. T denotes the highest period at which the subject understands that she can evaluate exactly one more option.[14] Hence, $T+1$ is the period at which the person knows that her probability of finding an option that will impact her choice is zero. So, she understands that she will not be able to evaluate a new option and if she does not make a selection now, her earnings will be zero at that time.

We define a reservation utility, u^R, by modifying the Gittins-Weitzman index (Gittins, 1979; Weitzman, 1979) for $u(x, r)$. The reservation utility can be interpreted as a fictitious value that makes the subject indifferent between taking this value and evaluating one more option. The next result shows that optimal search is a cutoff strategy described by the reservation utility. A subject should keep searching as long as the best option in hand so far has a lower value than the reservation. We also show how the cost and gain/loss parameters, c, β, and γ affect the reservation utility with implications on the expected value of choice.

Result 1. *For any $r, \beta, \gamma, c > 0$, there is a unique reservation utility, u^R, such that for any $t \in \{1, ..., T\}$, it is optimal to select the highest value option that is found until $t-1$ if and only if this value is less than u^R; otherwise, searching more is optimal. This is the unique optimum strategy and u^R increases with β and γ and decreases with c.*

Result 1 describes the optimal search strategy of a decision maker in a search problem similar to the ones in our experiments. The proof constructs the marginal utility of searching one more period given the best option in hand so far. In a given period t, for a subject whose best option so far is u_t, the marginal expected utility of evaluating one more option rather than stopping search is described as a function of u_t. The intersection of this function with the cost of searching one more option gives

[14] In the experiment, each choice has ten options, hence $T \leq 10$.

the optimal reservation utility. Figure 2 illustrates this constructed function when there is a reference, r, denoted by the solid curve, and when there is no reference, denoted by the dotted curve. Note that the function has a kink at the reference when the reference is introduced. This is because the forces causing the shift on the left and right of r are different. If the value of the best option in hand so far is already above the reference itself, the introduction of the reference will increase the marginal utility of search due to the additional motivation of the gain utility. If it is below the reference, the subject will feel the loss in the presence of a reference, so the marginal utility of search increases both to avoid that loss and to potentially gain some amount above the reference. Due to this asymmetry, we see a kink at r in Figure 2.

Figure 2 also provides an example of a subject with a cost parameter of c, and shows how the optimal reservation shifts when there is no reference as in the Baseline and when there is a reference as in the Exogenous Treatment. Note that for every cost level, the optimal reservation level will be higher in the Exogenous Treatment than the Baseline as Figure 2 illustrates. So both those who search little or a lot without the reference will be motivated to search more with the reference since the shift occurs on the whole domain. This observation leads to Corollary 1.

Corollary 1. *The reservation utility is higher when there is a reference.*

Corollary 1 implies that a subject is expected to search more in the Exogenous Treatment than the Baseline and to find a better ranked option. This implication is summarized in Hypothesis 1.

Hypothesis 1. ***[Reference Effect]*** *For any rank level, the probability of choosing a better ranked option is higher in the Exogenous Treatment than that in the Baseline.*

Recall that the value of not searching in the initial period of the Exogneous and Endogenous Treatments are different. At period 0, while $u_0 = 0$ in the Exogenous Treatment, $u_0 = r$ in the Endogeneous Treatment. According to the optimal search strategy found in Result 1, a subject whose u^R is below r should not start the initial

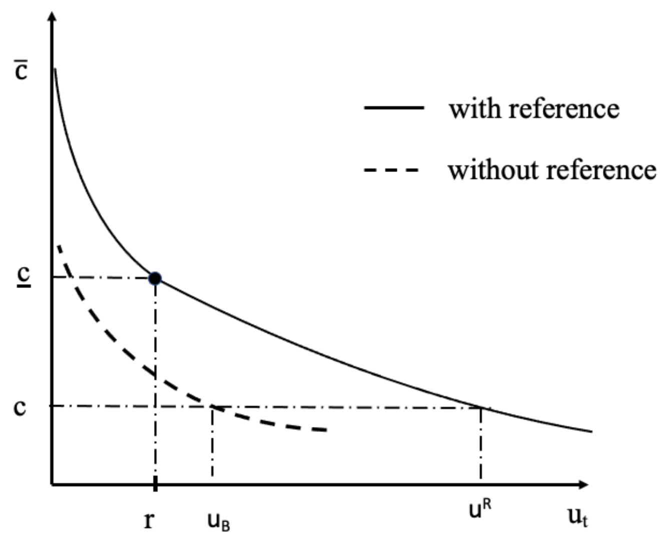


Figure 2: Marginal utility of searching given u_t and optimal reservation utility

Notes: The marginal utility of searching one more period is illustrated for the Baseline where there is no reference (dotted line) and for the Treatments where there is a reference (solid line). Optimal reservation utility is found at the intersection of these functions at the cost of search, c; these are given by u_B for the Baseline and u^R in the Treatments. Cut-off costs $(\underline{c}, \overline{c})$ are provided for reference and are utilized in Result 2.

search in the Endogenous Treatment. Since the reservation utility decreases with cost, one can find a cutoff cost level to determine who will start searching in this treatment. As it can be seen in Figure 2, that cutoff is $\underline{c}$ which corresponds to $u^R = r$. For a subject whose cost is in $(\underline{c}, \overline{c})$ the value of default option will be above her reservation utility, and hence, she will take the default option rather than searching in the Endogeneous Treatment. However, such a subject would prefer searching in the Exogeneous Treatment. This causes those subjects with high costs to drop out from search in the Endogenous Treatment. The next result states this selection result.[15]

Result 2. *For a given pair of gain/loss parameters, there is a range of cost, $(\underline{c}, \overline{c})$, such that a subject with $c \in (\underline{c}, \overline{c})$ would search in the Exogenous Treatment but not in the Endogenous Treatment.*

For our experiment, Result 2 implies that the expected reservation utility of the subjects who rejected the default will be higher in the Endogenous treatment since those with the low reservation will take the default. Hence, finding a better-ranked option is more likely to happen in the Endogenous treatment than the Exogenous one. This leads to Hypothesis 2.

Hypothesis 2. ***[Self-selection Effect]*** *For any rank level, the probability of choosing a better-ranked option is higher in the Endogenous treatment than in the Exogenous treatment.*

4 Results

Throughout the analysis, we refer to the choice from the 10 presented options as "active choice". Choosing the default in the Endogenous Treatment or receiving the

[15]A similar selection result can be written in terms of the gain/loss parameters since these parameters are the two other sources of heterogeneity affecting the initial search decision in the model. Note also that the model assumes risk-neutrality for simplicity, so another selection result could be derived in terms of risk attitudes in an extension of the current work. As we mention in Section 4, our results are inconsistent with an interpretation of selection exclusively based on risk attitudes.

default as the result of randomization in the Exogenous one are not considered active in this terminology. While the latter is clearly not an active choice, as the computer assigns the default to the subject, we apply this terminology to the Endogenous treatment as well in order to distinguish between choosing after search and settling with the default without seeing any other option (see also Chetty et al., 2014).

We start our analysis with the entry decisions in the Endogenous Treatment. Table 2 presents descriptive statistics for the Active Choice Selection Rate, which we define as the percentage of decision problems (out of 20) where a subject chose to see their options and make a choice (i.e., they did not choose the default option).

Several trends emerge. Overall, subjects engage in "active choice" in roughly 81.5% of all decision problems. They are more likely to search actively in the earlier rounds by about 5 percentage points. At one extreme, out of 92 subjects, 4 *always* chose the default. At the other, 55 subjects (59.78%) chose actively for all 20 decision problems, always forgoing the default option. These subjects are our first evidence for the self-selection effect in line with the prediction of Theorem 2. We take this as evidence that the most meaningful comparison between our treatments restricts attention only to these subjects who rejected the default (i.e., chose actively) in all 20 decision problems *and* chose one of the available options in the active choice problem (i.e., did not time out). In this way we more closely mimic one-shot real-world (e.g., procurement auction) or laboratory (e.g., tournament) entry decisions that have been previously studied in the body of literature.

Furthermore, the high rate of Active Choice in this treatment indicates that the subjects found the decision problem moderately easy and hoped to find better options than the default in their active choices. As we mentioned in Section 2, we intentionally chose a relatively low value for the default option to have enough observations for endogenous entry, but we did not set it too low so as to have meaningful self-selection. Table 2 shows that our design choices succeeded in these goals since neither i) everyone always chose the *default option* nor ii) everyone always *chose actively*.

Table 2: Entry Decisions in Endogenous Treatment

	Mean	SD	Min	p25	Median	Max
Active Choice Selection Rate	.815	.303	0	.7	1	1
N	92					

Notes:
Active Choice Selection Rate defined as percentage of decision problems where the subject made an active choice (i.e. did not choose the default option). 55 of 92 subjects (59.78%) always chose Active Choice. 4 of 92 subjects (4.35%) never chose Active Choice.

Table 3 reports the frequency with which subjects choose the highest-valued option (Correct Rate) in each treatment. There is evidence of a selection effect: the Correct Rate is highest in the Endogenous treatment at 79.3%, nearly 8 percentage points higher than in the Exogenous treatment. However, there is only weak evidence of reference dependence at this extensive margin: while the Correct Rate is higher in the Exogenous treatment (71.6%) than in the Baseline (68.8%), this difference is not statistically significant. Table 3 reports the Correct Rate aggregating all the rounds, as subjects are no more likely to choose the optimal option in earlier rounds than in later ones.

To look at the intensive margin of welfare differences between treatments, we examine the discrete rank of the chosen option conditional on choosing sub-optimally (i.e., not choosing the highest-valued option). The distributions of the Rank of Chosen Option for the Baseline and Exogenous Treatments are reported in Figure 3. A

Table 3: Correct Rate by Treatment

		Baseline	Exogenous	Endogenous
Correct Rate	Mean	68.8%	71.6%	79.3%
	Std. Dev.	(46.4)	(45.1)	(40.6)
	Obs.	1300	1501	1100
	p-values		vs Baseline: 0.411	vs Exogenous: 0.002

Notes:
p-values are calculated via logistic regression with subject-level clustering.

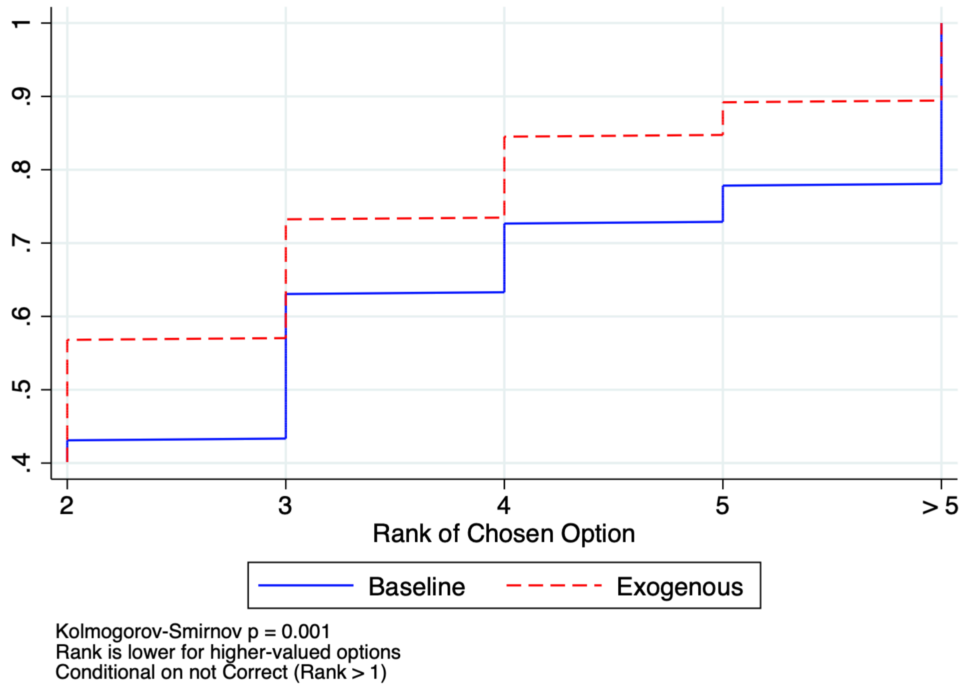


Figure 3: CDF of Rank of Chosen Option: Baseline vs Exogenous Treatment

Notes: Rank is lower for higher-valued options. To emphasize visually where the CDFs are different, we pool the observations where the rank of the chosen option is > 5 into a single category. The reported Kolmogorov-Smirnov p-values are calculated using the entire distribution.

Kolmogorov-Smirnov test indicates a significant difference between the distributions ($p = 0.001$). Since the only difference between Active Choice in the Baseline and the Exogenous treatment is that, in the latter, a subject was aware of an exogenously foregone default option, any resultant welfare change between these two environments is attributable to this default option serving as a reference during Active Choice. We find that subjects are more likely to choose better ranked (i.e., higher valued) options in the Exogenous treatment relative to the Baseline. This supports Hypothesis 1.[16]

To test if there is self-selection in addition to a reference effect, we perform the

[16] The Kolmogorov-Smirnov test assumes independence of the observations, which may not hold in our data given multiple observations per subject. Our results are qualitatively similar when we test for treatment differences in the Rank of Chosen Option conditional on sub-optimal choice using ordered logistic regressions with subject-level clustering.

rank comparison for the Exogenous and Endogenous treatments in Figure 4. Recall that the only difference between the Exogenous and Endogenous treatments is that in the latter, subjects can freely choose the default option instead of it being exogenously assigned. The value of the default option serves as a reference in both. Therefore, any welfare difference between these two treatments is attributable to selection. Note that for any ranking level, the CDF of the Endogenous treatment is higher than that of the Exogenous one. The two CDFs are significantly different according to a Kolmogorov-Smirnov test with ($p = 0.003$). This indicates that subjects are more likely to choose better ranked (i.e., higher valued) options in the Endogenous treatment relative to the Exogenous treatment. This finding supports Hypothesis 2.[17]

In addition to investigating the welfare effects of the Endogenous and Exogenous treatments using the Rank of the chosen option, we alternatively consider monetary gains. "Gain" is defined as the percentage of available monetary gains that the subject attained above the mean option value within a given decision problem. Formally, in decision problem i, let v_i^* be the value of the optimal option, $\bar{v}_i$ be the mean value of the available options, and v_i be the value of the option that the subject chose. We then define Gain as follows:

$$\text{Gain}_i = \frac{v_i - \bar{v}_i}{v_i^* - \bar{v}_i}$$

Figure 5 presents distributions of Gain across the Baseline, Endogenous, and Exogenous Treatments, conditional on sub-optimal choice, mirroring the above Rank analysis. These distributions tell a similar story to those for Rank in Figures 3 and 4. First, subjects experience more Gain in the Exogenous Treatment relative to the Baseline, indicative of a reference effect. Additionally, they experience more Gain in the Endogenous Treatment relative to the Exogenous one, consistent with the self-selection effect.[18]

[17]Results are qualitatively similar when we test for treatment differences in the Rank of Chosen Option, conditional on sub-optimal choice using ordered logistic regressions with subject-level clustering.

[18]Results for Gain analysis are qualitatively similar when we investigate treatment effects via OLS regression with subject-level clustering.

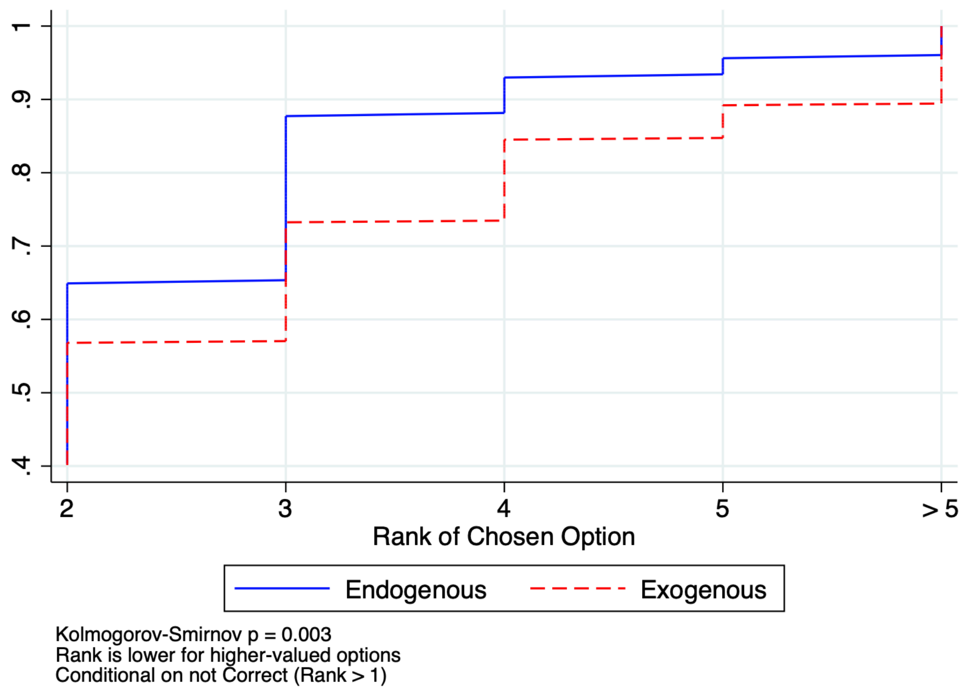
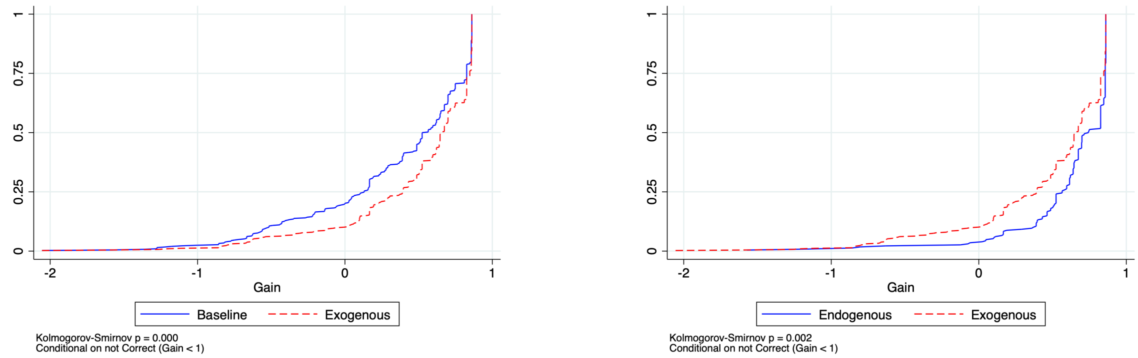


Figure 4: CDF of Rank of Chosen Option: Exogenous vs Endogenous Treatment

Notes: Rank is lower for higher-valued options. To emphasize visually where the CDFs are different, we pool the observations where the rank of the chosen option is > 5 into a single category. The reported Kolmogorov-Smirnov p-values are calculated using the entire distribution.



(a) Baseline vs Exogenous

(b) Exogenous vs Endogenous

Figure 5: Gain Distributions

Notes: Gain is calculated as the percentage of the available monetary gain above the mean option value captured by the choice of the subject, i.e. $\text{Gain}_i = \frac{v_i - \bar{v}_i}{v_i^* - \bar{v}_i}$ where v_i is the value of the chosen option, v_i^* is the value of the optimal option in the decision problem, and $\bar{v}_i$ is the mean option value in the decision problem.

As additional support to the results derived from choice data, we look at decision time data. Since subjects are forced to choose actively both in the Exogenous Treatment and the Baseline, searching skills are expected to be similar in these two cases. On the other hand, the reference presented in the Exogeneous Treatment increases the reservation utility of the optimal search with respect to that in the Baseline according to Theorem 1. Since the higher reservation would mean a longer search in expectation when we keep the skill level fixed, the average decision time in the Exogenous Treatment is predicted to be higher. We observe that the subjects indeed spend *more* time in the Exogenous Treatment relative to the Baseline (31.18 vs. 23.73 seconds, respectively; Mann-Whitney $p < 0.001$).

In the Endogenous Treatment, while the reference effect predicts more search (due to higher optimal reservation), the self-selection effect may increase or decrease the decision time. Since only the lower-cost subjects are self-selecting in this case, these subjects might also be faster in evaluating each option. On the other hand, self-selection also predicts higher reservation on average for these actively searching subjects, i.e., evaluation of more options in a given decision problem. So it may take these subjects longer to submit a final decision even if they are faster in the evaluation of each option. In the data, we see that the actively searching subjects in the Endogenous Treatment spend on average 26.60 seconds on a decision problem and this is significantly faster decision time than in the Exogenous Treatment (Mann-Whitney $p<0.001$).[19] Thus, arguably, the lower-cost subjects are skillful and faster.

5 Conclusion

In this paper we document that the presence of a default option can affect choice through two channels: self-selection and reference-dependence. Both effects lead to options with higher objective values being chosen more frequently by decision makers who actively search. While the former channel is strategic and expected to be presented by anyone with or without reference dependent utilities, the latter one is a psychological motive and can be explained by gain/loss utilities.

Our results suggest new ways in which default options can be powerful modulators of choice. Our theoretical analysis provides optimal search strategies of decision makers with reference dependent utilities in the presence of a default option or other references. A large and growing body of literature investigates the welfare effects of reference dependence and default options as well as optimal default design (e.g., Carroll et al., 2009; Bernheim et al., 2015; Bernheim and Gastell, 2020; Goldin and Reck, 2020; Choukhmane, 2021; Goldin and Reck, 2022; Reck and Seibold, 2022). Incorporating these results into optimal default design problems should be a fruitful exercise both theoretically and empirically. Our findings point out that choice architects should not only set the reference optimally, but also decide whether it can be voluntarily opted out or not since the former one may activate the self-selection effect.

In this paper we evaluated the choice change caused by default in terms of the

[19]Note also that subjects spending less time in Endogenous than in Exogenous, but making better decisions, is not consistent with an interpretation of selection exclusively based on risk attitudes.

objective ranking of the chosen option, amount of monetary gains, and time invested in search. We leave it for future research to estimate and incorporate psychological effects of default into welfare analysis.

References

Abaluck, J. and A. Adams-Prassl (2021): "What do consumers consider before they choose? Identification from asymmetric demand responses," *Quarterly Journal of Economics*, 136.

Bajari, P. and A. Hortaçsu (2003): "The winner's curse, reserve prices, and endogenous entry: Empirical insights from eBay auctions," *RAND Journal of Economics*, 329–355.

Bernheim, B. D., A. Fradkin, and I. Popov (2015): "The welfare economics of default options in 401 (k) plans," *American Economic Review*, 105, 2798–2837.

Bernheim, B. D. and J. M. Gastell (2020): "Optimal default options: The case for opt-out minimization," Tech. rep., National Bureau of Economic Research.

Bo, P. D., A. Foster, and L. Putterman (2010): "Institutions and Behavior: Experimental Evidence on the Effects of Democracy," *American Economic Review*, 100, 2205–29.

Boosey, L., P. Brookins, and D. Ryvkin (2020): "Information disclosure in contests with endogenous Entry: An experiment," *Management Science*, 66, 5128–5150.

Bowman, D., D. Minehart, and M. Rabin (1999): "Loss aversion in a consumption–savings model," *Journal of Economic Behavior and Organization*, 38, 155–178.

Bushong, B. and T. Gagnon-Bartsch (2022): "Reference dependence and attribution bias: evidence from real-effort experiments," *American Economic Journal: Microeconomics*.

Caplin, A., M. Dean, and D. Martin (2011): "Search and satisficing," *American Economic Review*, 101, 2899–2922.

Carroll, G. D., J. J. Choi, D. Laibson, B. C. Madrian, and A. Metrick (2009): "Optimal defaults and active decisions," *The quarterly journal of economics*, 124, 1639–1674.

Chadd, I., E. Filiz-Ozbay, and E. Y. Ozbay (2021): "The relevance of irrelevant information," *Experimental Economics*, 24, 985–1018.

Chen, D. L., M. Schonger, and C. Wickens (2016): "oTree - An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88–97.

Chetty, R., J. N. Friedman, S. Leth-Petersen, T. H. Nielsen, and T. Olsen (2014): "Active vs. passive decisions and crowd-out in retirement savings accounts: Evidence from Denmark," *Quarterly Journal of Economics*, 129, 1141–1219.

Choukhmane, T. (2021): "Default options and retirement saving dynamics," *working paper*.

DellaVigna, S., A. Lindner, B. Reizer, and J. F. Schmieder (2017): "Reference-dependent job search: Evidence from Hungary," *The Quarterly Journal of Economics*, 132, 1969–2018.

Ericson, K. M. (2014): "Consumer inertia and firm pricing in the Medicare Part D prescription drug insurance exchange," *American Economic Journal: Economic Policy*, 6, 38–64.

Gabaix, X., D. Laibson, G. Moloche, and S. Weinberg (2006): "Costly information acquisition: Experimental analysis of a boundedly rational model," *American Economic Review*, 96, 1043–1068.

Gagnon-Bartsch, T. and B. Bushong (2022): "Learning with misattribution of reference dependence," *Journal of Economic Theory*, 203, 105473.

Gittins, J. C. (1979): "Bandit processes and dynamic allocation indices," *Journal of the Royal Statistical Society: Series B (Methodological)*, 41, 148–164.

Goldin, J. and D. Reck (2020): "Revealed-preference analysis with framing effects," *Journal of Political Economy*, 128, 2759–2795.

——— (2022): "Optimal defaults with normative ambiguity," *Review of Economics and Statistics*, 104, 17–33.

Kahneman, D. and A. Tversky (1979): "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47, 263–91.

Kőszegi, B. and M. Rabin (2006): "A model of reference-dependent preferences," *Quarterly Journal of Economics*, 121, 1133–1165.

Langtry, A. (2022): "Keeping up with 'The Joneses': reference dependent choice with social comparisons," *American Economic Journal: Microeconomics*.

Levav, J., M. Heitmann, A. Herrmann, and S. S. Iyengar (2010): "Order in product customization decisions: Evidence from field experiments," *Journal of Political Economy*, 118, 274–99.

Levin, D. and J. L. Smith (1994): "Equilibrium in auctions with entry," *American Economic Review*, 585–599.

Madrian, B. C. and D. F. Shea (2001): "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior," *Quarterly Journal of Economics*, 116, 1149–1187.

O'Donoghue, T. and C. Sprenger (2018): "Reference-dependent preferences," in *Handbook of Behavioral Economics: Applications and Foundations 1*, Elsevier, vol. 1, 1–77.

Reck, D. and A. Seibold (2022): "The welfare economics of reference dependence," *working paper*.

Seibold, A. (2021): "Reference points for retirement behavior: Evidence from german pension discontinuities," *American Economic Review*, 111, 1126–65.

Weitzman, M. L. (1979): "Optimal search for the best alternative," *Econometrica*, 641–654.

A Proofs

Before proving Theorem 1, we will define two functions which will prove to be useful later and study their properties. Define $f : \mathbb{R}_+ \to \mathbb{R}_+$ such that

$$f(u) := (1+\gamma)\int_u^\infty (x-u)\,dF(x)$$

If $f(r) \leq c$[20], define $g : [0, r] \to \mathbb{R}_+$

$$g(u) := \int_u^r (1+\beta)(x-u)\,dF(x) + \int_r^\infty (x-u) + \beta(r-u) + \gamma(x-r)\,dF(x)$$

Lemmata 1 and 2 find the reservation utility levels by setting each of these functions equal to the search cost and study the properties of these reservation utilities.

Lemma 1. *There is unique $u_f \in \mathbb{R}_+$ such that $f(u_f) = c$ and if $u_f < r$ there is unique $u_g > u_f$ such that $g(u_g) = c$.*

Proof of Lemma 1. Note that since F has a continuous density, f and g are continuous. It is also straight forward to show that both functions are decreasing in u.

Note that $f(0) = (1+\gamma)E[x] > c$ and $\lim_{u\to\infty} f(u) = 0 < c$. Since f is monotone and continuous the solution of $f(u) = c$ uniquely exists. Call this solution as u_f.

When $f(r) \leq c$ we have $g(r) = f(r) \leq c$. Also note that $g(0) = E[x] + (\text{a positive term}) > c$ Since g is continuous and monotone, there exists a unique solution to $g(u) = c$. Call this solution u_g.

[20]Since f is a decreasing function, $f(r) \leq c$ means that r needs to be sufficiently large for g to enter our analysis.

Moreover, when $u_f < r$ we have

$$
\begin{aligned}
g(u_f) - f(u_f) &= [\int_{u_f}^{r} (1+\beta)(x-u_f)\, dF] + [\int_{r}^{\infty} (x-u_f) + \beta(r-u_f) + \gamma(x-r)\, dF \\
&\qquad - [(1+\gamma)\int_{u_f}^{\infty} (x-u_f)\, dF] \\
&= \int_{u_f}^{r} (\beta-\gamma)(x-u_f) + \int_{r}^{\infty} (x-u_f)(-\gamma) + \beta(r-u_f) + \gamma(x-r)\, dF \\
&= \int_{u_f}^{r} (\beta-\gamma)(x-u_f) + \int_{r}^{\infty} (\beta-\gamma)(r-u_f)\, dF \\
&> 0
\end{aligned}
$$

The last inequality is implied by the assumption that $\beta > \gamma$.

Then we have $g(u_f) > f(u_f) = c = g(u_g)$. Since g is a decreasing function, we have $u_g > u_f$ when $u_f < r$.

□

Lemma 2. *u_f and u_g are monotone in the parameters of the model as follows:*

i) u_f increases with γ and decreases with c,

ii) u_g increases with β and γ and decreases with c.

decreases with c; $u_{r\beta}$ increases with β and decreases with c.

Proof of Lemma 2. Since u_f and u_g are solutions to decreasing functions of f and g at c, respectively, these solutions must decrease with c.

Note that f shifts upwards when γ increases. Similarly, g shifts upwards when β or γ (or both) increases. If these decreasing functions shift upwards, the values at which they intersect with c (i.e., u_f and u_g) increase b. □

Lemmata 3 and 4 describe the optimal search strategy based on the size of the reference r.

Lemma 3. *Let $r < u_f$ then in any period $1 \leq t \leq T$, searching one more round is weakly better than stopping the search if and only if the value of best option in hand at time t offers less than u_f.*

Proof of Lemma 3. Let u_t be the value of best option in hand at time t. Note that the utilities of stopping the search at that moment and searching exactly one more round are

Stop $= u_t - \beta(r-u_t)^+ + \gamma(u_t-r)^+$

Search $= E\left[max\{x-\beta(r-x)^+ + \gamma(x-r)^+, u_t - \beta(r-u_t)^+ + \gamma(u_t-r)^+\}\right] - c$
where $(y)^+ = max\{y, 0\}$. Then

$$Search{-}Stop = \int_{u_t}^{\infty} x{-}u_t{-}\beta\left[(r-x)^+ - (r-u_t)^+\right]{+}\gamma\left[(x-r)^+ - (u_t-r)^+\right]\, dF(x){-}c$$

Case 1: Let $u_t \leq u_f$ then there are two possibilities:
Case 1a: If $r \leq u_t \leq u_f$ Then searching is better since

$$\begin{aligned} Search - Stop &= \int_{u_t}^{\infty} (x-u_t) - 0 + \gamma(x-u_t)\, dF(x) - c \\ &= f(u_t) - f(u_f) \\ &\geq 0 \qquad\qquad \text{(Since f is decreasing.)} \end{aligned}$$

Case 1b: If $u_t \leq r \leq u_f$ Then searching is better since

$$\begin{aligned} Search - Stop = &\int_{u_t}^{r} (x-u_t) + \beta(x-u_t)\, dF(x) + \int_{r}^{\infty} (x-u_t) + \beta(r-u_t) + \gamma(x-r)\, dF(x) - c \\ &= g(u_t) - f(u_f) \\ &\geq g(r) - f(u_f) \qquad\qquad \text{(Since } g \text{ is decreasing.)} \\ &= f(r) - f(u_f) \\ &\geq 0 \end{aligned}$$

Note that if $u_t = u_f$ in the above cases, the subject is indifferent between searching one more round and stopping.
Case 2: If $u_t > u_f$ then $u_t > r$ by the assumption of the Lemma. Then the utilities of stopping the search at that moment and searching one more round are

Stop $= u_t - \beta(r-u_t)^+ + \gamma(u_t-r)^+ = u_t + \gamma(u_t - r)$

Search $= \int_0^{u_t} u_t + \gamma(u_t-r)\, dF(x) + \int_{u_t}^{\infty} x + \gamma(x-r)\, dF(x) - c$
Then stopping is better since

$$\begin{aligned} Search - Stop &= \int_{u_t}^{\infty} (1+\gamma)(x-u_t)\, dF(x) - c \\ &= f(u_t) - f(u_f) \\ &< 0 \qquad\qquad \text{(Since } f \text{ is decreasing.)} \end{aligned}$$

$\square$

Lemma 4. *Let $r \geq u_f$ then in any period $1 \leq t \leq T$, searching one more round is weakly better than stopping the search if and only if the value of best option in hand at time t offers less than u_g.*

Proof of Lemma 4. Let u_t be the value of best option in hand at time t.
Case 1: If $u_t \leq u_g$, then $u_t \leq u_g \leq r$ by the proof of Lemma 1. Then the utilities of stopping the search at that moment and searching one more round are

Stop $= u_t - \beta(r-u_t)^+ + \gamma(u_t - r)^+ = u_t - \beta(r-u_t)$

Search $= \int_0^{u_t} u_t - \beta(r-u_t)\, dF(x) + \int_{u_t}^{r} x - \beta(r-x)\, dF(x) + \int_r^{\infty} x + \gamma(x-r)\, dF(x) - c$

Searching is better than stopping since

$$\begin{aligned} Search - Stop &= \int_{u_t}^{r} x - u_t + \beta(x-u_t)\, dF(x) + \int_r^{\infty} x - u_t + \beta(r-u_t) + \gamma(x-r)\, dF(x) - c \\ &= g(u_t) - g(u_g) \\ &\geq 0 \qquad\qquad \text{(Since } g \text{ is decreasing.)} \end{aligned}$$

Note that if $u_t = u_g$ the subject is indifferent between searching one more round and stopping.
Case 2: If $u_t > u_g$ then there are two cases relevant for the analysis:
Case 2a: If $u_t > r \geq u_g$, then recall that we also assumed $r \geq u_f$. So we have $u_t > r \geq u_g \geq u_f$ since by the proof of Lemma 1 $u_g \geq u_f$. Then in both searching and stopping strategies there will only be gain utilities but no loss utilities due to the reference. The difference between the utilities of searching and stopping strategies becomes

$$\begin{aligned} Search - Stop &= \int_{u_t}^{\infty} (1+\gamma)(x-u_t)\, dF(x) - c \\ &= f(u_t) - f(u_f) \\ &=< 0 \end{aligned}$$

Hence, stopping is better for Case 2a.
Case 2b: If $r \geq u_t$, then $r \geq u_t > u_g \geq u_f$. Then the utilities from searching one more period and stopping are

Search $= \int_0^{u_t} u_t - \beta(r-u_t)\, dF(x) + \int_{u_t}^{r} x - \beta(r-x)\, dF(x) + \int_r^{\infty} x + \gamma(x-r)\, dF(x) - c$

Stop $= u_t - \beta(r-u_t)$

Then stopping is better because

$$\begin{aligned} Search - Stop &= \int_{u_t}^{r} x - u_t + \beta(x - u_t)\, dF(x) + \int_{r}^{\infty} x - u_t + \beta(r - u_t) + \gamma(x - r)\, dF(x) - c \\ &= g(u_t) - g(u_g) \\ &< 0 \end{aligned}$$

This concludes the proof. □

We now turn to the proof of Theorem 1.

Proof of Theorem 1. For any $r, \beta, \gamma,$ and $c \geq 0$, define the reservation utility u^R as follows:

$$u^R = \begin{cases} u_f, & \text{if } r < u_f \\ u_g, & \text{if } r \geq u_f \end{cases}$$

where u_f and u_g are defined in Lemma 1. Then from Lemmata 3 and 4, the threshold strategy defined in the statement is optimal for one and only one period extended search. Note that the reservation utility is independent of which period the subject is. Hence, at a given period if stopping is better than searching exactly one more period, i.e., $u_t > u^R$ is satisfied in that period, it must be better than the expected return on search for multiple periods as well. The same is true for $u_t \leq u^R$. □

Proof of Corollary 1. First note that since there is no reference in the Baseline, the equilibrium strategy for that case is equivalent to the one described above for $\beta = \gamma = 0$. That means the reservation utility in the Baseline, u_B, is the value of u_f for the case of $\gamma = 0$. Then by Lemma 2, $u_f > u_B$ for any $\gamma > 0$.

When the reservation utility is defined by u_g in the Exogenous treatment, then from the proof of Lemma 1 $u_g > u_f$. Then together with the observation above we have $u_g > u_f > u_B$.

So u^R defined above will be strictly higher than u_B for both cases. With a higher reservation utility in the Exogenous case than the Baseline, a subject in the Baseline will be expected to search less. Hence, it is expected to see a better ranked option to be chosen in the Exogenous Treatment. □

Proof of Theorem 2. Note that, for a fixed choice problem, a searching subject after period 1 in both the Exogenous and Endogenous Treatments have the same optimal reservation utility as described by Theorem 1. So the only difference between the two treatments is the selection that may happen at time $t = 0$, i.e., at the initial search.

In the Exogenous Treatment anyone with a positive reservation, $u^R \geq 0$, will search, i.e. $c \leq g(0)$. Call this cutoff cost level $\bar{c} := g(0)$.

In the Endogenous Treatment anyone with a reservation above the reference, $u^R \geq r$, will search, i.e. $c \leq f(r)$ [21]. Call this cutoff cost level $\underline{c} := f(r)$. Since f is decreasing, $\underline{c} < \bar{c}$ for positive gain/loss parameters.

Hence, for a given decision problem, subjects whose cost is in the interval of $(\underline{c}, \bar{c})$ would start the initial search in the Exogenous Treatment but not in the Endogeneous one.

$\square$

[21] Recall that by the definition of f and g, $f(r) = g(r)$. Hence it does not matter which function is used to determine this cutoff search cost

B Instructions: [Endogenous Treatment]

Here we present instructions for the Endogenous Treatment only, as they contain all relevant information that pertains to all treatments. In the Baseline, there was no mention of an outside option at all. In the Exogenous Treatment, it was made clear that the outside option would be given to the subject with 50% probability (i.e. they were unable to choose the outside option themselves).

Instructions

In this study, you will make decisions in each of 20 Decision Problems.

In each Decision Problem, you may see a screen that is similar to what is displayed below:

Please select one of the following options.

If this problem is chosen for payment, you will be paid for the number of # displayed for the option you choose.

Option 1: %%

Option 2: #%%#%##%##%%##%%%%#%%%#%%%#%%#%%#%%%%%#%%%#%%%%#%%

Option 3: %%#%%##%%%%%%%#%%%%%%%%%%%%%%%%%%%#%%%%%%#%%%%%%%%

Option 4: #%%%%%%#%%###%%%%%#%%#%%%##%##%%#%%%#%##%##%#%%%#%

Option 5: %##%#%#%%%#%##%##%%##%%%%%%##%%%%%##%#%%#%##%#%%##

Option 6: %####%%#%#%#%%%#%%%%##%%#%%%###%%%%%#%#%##%%%#%##%

Option 7: %%#%####%%%%%%#%%%%%#%%%#%%%%%%%%%%%%%#%##%%%%%%%%

Option 8: %%#%##%#%%%%#%#%#%%%%%%%##%##%%%%##%%#%%##%%%%%%%#%

Option 9: %%#%%%%%##%#%%#%#%%%%#%%%%#%###%%%#%%%%%%%%#%%%%##

Option 10: %%%%%##%##%%%%%####%##%#%##%%%%###%#%%%###%%%%%%%#

On this screen, you can see some "options" which are just displayed as a combination of pound signs (#) and percent signs (%). Your job is to choose one of these options in the Decision Problem.

Choosing an option earns you points which will be converted to cash at the end of the experiment at a rate of 10 points per USD and paid to you. The number of points an option will earn you is equal to the number of pound signs (#) in the option.

On the next page, we'll go through an example of one option and the number of points it would earn you.

Next

Instructions

An example option is displayed below:

####%#%%##%##%#%%%###%####%%###%#%%#%#%#%%%%%#%####

Notice that this option has 50 characters, 28 of which are pound signs (#). Then you would earn 28 points if you chose this option in the Decision Problem.

Next

Instructions

At the beginning of each Decision Problem, you are going to be given a choice between two courses of action:
1. See 10 options, each with 50 characters (i.e. #'s and %'s) and earn points by choosing from those options
2. Take an **outside option** that earns you 14 points and skip seeing any displayed options

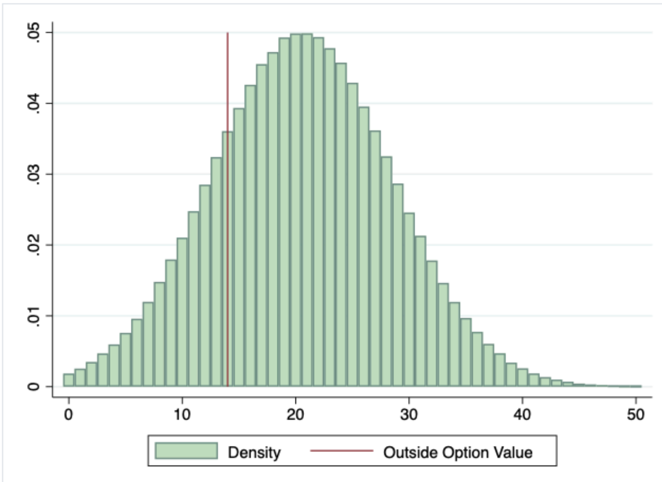
This **outside option** has no display and earns you 14 points if you choose it. Choosing the **outside option** effectively means that you are skipping making any choices in the Decision Problem, opting to take 14 points instead of earning them by selecting a displayed option.

You will be given this choice in **every** Decision Problem. So if you decide to take the **outside option** in one Decision Problem, you can still choose to see your displayed options in a later Decision Problem.

Next

Instructions

All of the option values come from the probability distribution displayed below:



In order to generate options for each Decision Problem, we drew 10 of them randomly using the distribution above. We then checked whether there were multiple options with the highest value (i.e the highest number of #s). If there were, we drew 10 again from the same distribution. We repeated this process for each Decision Problem until each Decision Problem had a unique option with maximum value.

Note also where the value of the **outside option** is in the distribution above.

Next

Instructions

Whenever you see the 10 displayed options that you can choose, you will only have 120 seconds to make a choice.

To make a choice you must click on the option you are choosing and then click the Next button on the screen.

If you do not submit a choice of option in the Decision Problem before your time is up, you will earn 0 points for that Decision Problem.

Next

Instructions

At the end of the study, one of the 20 Decision Problems you completed will be chosen at random and you will **only** be paid for the points that you earned in that Decision Problem.

If you chose to see your displayed options for that Decision Problem, you will be paid the number of points awarded by the option that you chose in that Decision Problem. Remember that you earn 0 points if you do not choose an option and click Next in the time allotted.

If you chose the **outside option** for that Decision Problem, you will be paid for the 14 points that you earned.

You will not know which Decision Problem will be chosen at random for payment while you are making decisions. So it is in your best interest to act as if each Decision Problem is the one for which you will be paid.

Clicking on the Next button below will bring you to the first Decision Problem.

Next

Decision Problem: 1

In this Decision Problem, you could see 10 options, each with 50 characters.
Or, you could take an outside option that will earn you 14 points and not see any of these options.

Would you like to take the outside option?

○ I want to choose for myself, show me my options

◉ I want to take the outside option of 14 points

Remember, if you take the outside option, you will earn 14 points and will not see options for this Decision Problem.
If you don't, you will move on the Decision Problem where you will choose from among the displayed options.

Next