The Relevance of Irrelevant Information *

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

September 25, 2020

Abstract

This paper experimentally investigates the effect of introducing unavailable alternatives and irrelevant information regarding the alternatives on the optimality of decisions in choice problems. We find that the presence of unavailable alternatives and irrelevant information generates suboptimal decisions with the interaction between the two amplifying this effect. Irrelevant information in any dimension increases the time costs of decisions. We also identify a "preference for simplicity" beyond the desire to make optimal decisions or minimize time spent on a decision problem.

JEL Codes: D03, D83, D91

Keywords: Presentation set, bounded rationality, simplicity, costly ignorance, free disposal of information

*We thank Gary Charness, Mark Dean, Allan Drazen, Daniel Martin, Yusufcan Masatlioglu, Pietro Ortoleva, Ariel Rubinstein, and Lesley Turner for helpful comments and fruitful discussions. We also would like to thank our anonymous reviewers for useful suggestions.

[†]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

In many decision problems, unavailable options along with irrelevant attributes are presented to decision makers. For example, consider a new employee of a large firm in the United States who must choose a health insurance plan. Among the many plans listed in their benefits handbook are some plans that are only available to employees of a high enough rank (e.g. team leads, managers, vice presidents) and so are "unavailable" to this new employee. Nevertheless, they can see premiums, coverage amounts, co-pays, etc. for these unavailable plans in the same way that they can see this information for plans that the employee can actually choose. Additionally, even among these plans some of this information might not be valuable. For example, if this new employee takes no regular specialty medication and always chooses generic medications, coverage for branded prescription drugs is irrelevant.

Consider some additional examples of unavailable alternatives:[1] In a restaurant menu, unavailable items may still be listed in the menu with a sold out note. A local event ticket website may list events that are sold-out. Also, consider some more examples of irrelevant attributes: Insurance coverage for care related to pregnancy may be presented to someone who could never get pregnant. The US Food and Drug Administration requires standardized nutrition label on food and beverage packages including fat, cholesterol, protein, and carbohydrate even when they are 0%, such as for a bottled water. Smartphones will list available service providers, even though this set will not vary across available smartphones.[2] From the perspective of classical rational choice theory, decision makers have *free disposal* of irrelevant information: they can costlessly ignore unavailable options and irrelevant attributes, and hence the presentation of such irrelevant information would not lead to different choices than those made when it is not presented. We experimentally demonstrate that the presentation set matters, providing evidence that the free disposal of irrelevant information is a non-trivial assumption in many contexts.

Our experiment is designed to test the effects of presenting irrelevant information in two di-

[1]Note that in all of these examples, the firm/regulatory agency in question may have separate incentives for providing irrelevant information. These can be statutory (as in cases of regulated information provision), strategic (e.g. a firm may provide distracting irrelevant information to hide negative attributes), or because of dynamic considerations (e.g. an item may not be available currently, but the firm wants to signal the possibility that it is available in the future). We do not directly consider the firm's incentives in the current work, instead focusing on pure effect of irrelevant information on choice.

[2]An attribute that does not vary across available options may be *utility* relevant, but it is certainly not *decision* relevant information in that it does not meaningfully distinguish one good from another.

mensions. In a differentiated product setting, the decision problems presented to subjects vary according to a) the presentation of options in a set of alternatives that can never be chosen (hereinafter referred to as unavailable options) and b) the presentation of attributes that have no value (i.e. that enter into a linear utility function with an attribute-level coefficient of zero; hereinafter referred to as irrelevant attributes). We find significant evidence that the presence of unavailable options and irrelevant attributes can increase the frequency of sub-optimal choice and that this effect is amplified with the interaction between the two.

Furthermore, motivated by the variation in online shopping websites allowing consumers to sort on the products based on the attributes they consider relevant, as well as allowing them to exclude the unavailable alternatives, we ask if individuals are willing to pay to reduce the amount of irrelevant information presented to them. We show that subjects are willing to pay significant positive amounts not to see unavailable alternatives or irrelevant information. Such a payment is mainly due to the reduction in mistakes and time costs caused by the presence of unavailable options and irrelevant attributes. Nevertheless, individuals may have a "preference for simplicity" in the presentation of information implying an additional cost, a cognitive cost of ignoring the irrelevant information. In order to identify such a cognitive cost, we analyze the willingness to pay (WTP) of the subjects who always chose optimally, who don't make additional mistakes, and who experience no additional time costs in the presence of unavailable options and irrelevant attributes. Our results indicate that even these subjects are willing to pay positive amounts to change the presentation set.

To our knowledge, unavailable alternatives have only been studied in the context of the decoy effect, which is the presentation of an alternative that increases the preference for a target alternative. Although in a typical experiment on decoys, the decoy alternative is available in the choice set, Soltani et al. (2012) showed that displaying an inferior good during an evaluation stage, but making it unavailable at the selection stage, also generates the decoy effect. Also, the phantom decoy alternatives that are superior to another target option, but unavailable at the time of choice, increase the preference for the inferior target option (see e.g. Farquhar and Pratkanis (1993)). There are several meaningful differences between our experiment and this literature on decoy goods, phantom or otherwise. First, our experiment involves objective, rather than subjective payoffs, eliminating a possible channel through which phantom alternatives should affect choice. Second, much of the discussion in Farquhar and Pratkanis (1993) and related work concerns the effect that a phantom good can have on choice *when it is not recognized as a phantom.* Clearly, if an unavailable option is mistakenly viewed as available, it is plausible that this may affect choice in a number of theoretical settings. However, we ask a different question, namely, can irrelevant information affect choice when it is objectively presented as irrelevant?

Our experiment also complements the experimental literature investigating the effects of *relevant* information on choice optimality. In particular, Caplin et al. (2011) find that additional (available) options and increased "complexity" (additional relevant attributes in our context) lead to increased mistake rates.[3] Also, Reutskaja et al. (2011) present evidence from an eye-tracking experiment that subjects are unable to optimize over an entire set (given a large enough alternative set), but can optimize quite well over a subset (see also Gabaix et al. (2006)). One contribution of our work herein is to show that a similar effect is present for adding unavailable alternatives and increasing the number of irrelevant attributes.

In limited consideration models, the DM creates a "consideration set" from the *available* set of alternatives and then chooses from the maximal element of the "consideration set" according to some rational preference relation (see e.g. Masatlioglu et al. (2012), Manzini and Mariotti (2007; 2012; 2014), and Lleras et al. (2017)). Also, according to the boundedly rational model that focuses on attributes, the salience theory of choice, certain *relevant* attributes may appear to be "more salient" to a DM than others, causing them to be overweighted in the decision-making process (see Bordalo et al. (2012), Bordalo et al. (2013), and Bordalo et al. (2016)). Some other models of search in multi-attribute settings are also based on *available* options and attributes.[4] Several of these models of choice allow for a "pruning" stage, where the DM eliminates from consideration unavailable options or options that are dominated according to some binary relation. Attention-based models with such a pruning stage include Kőszegi and Szeidl (2012); Manzini and Mariotti (2007; 2012). In each of these models, unavailable options should have no effect on choice.[5]

[3]Oprea (2019) also looks at "complexity" of decision rules, though in a different context than what we consider herein.

[4]See Klabjan et al. (2014); Sanjurjo (2017); Richter (2017), for example.

[5]Several other models can be considered to have a "pruning" stage, though this element of the model is less explicit relative to the attention-based models mentioned here. For example, Bordalo et al. (2012; 2013; 2016) can be considered to treat irrelevant attributes as "pruned" in that they are de-facto treated with zero salience and, hence, ignored. Additionally, Kahneman and Tversky (1979) include an "editing" stage wherein lotteries are re-expressed by compressing payoff-equivalent states and therefore the lottery framing information of this form is "pruned." The latter model is less explicitly connected to our experiment, but is mentioned for posterity.

The rest of the paper is organized as follows. Section 2 explains the design of the experiments in detail. Sections 3 and 4 present the results for our main experiments and control experiments, respectively. We discuss our results and some of the implications thereof in Section 5 and Section 6 concludes.

2 Experimental Procedure

The experiments were run at the Experimental Economics Lab at the University of Maryland (EEL-UMD). All participants were undergraduate students at the University of Maryland. The data was collected in 14 sessions and there were two parts in each session. No subject participated in more than one session. Sessions lasted about 90 minutes each. The subjects answered forty decision problems in Part 1, and a subject's willingness to pay to eliminate unavailable options and irrelevant attributes were elicited in Part 2. In each session the subjects were asked to sign a consent form first and then they were given written experimental instructions (provided in Appendix A) which were also read to them by the experimenter. The instructions for Part 2 were given after Part 1 of the experiment was completed.

The experiment is programmed in z-Tree (Fischbacher, 2007). All amounts in the experiment were denominated in Experimental Currency Units (ECU). The final earnings of a subject was the sum of her payoffs in ten randomly selected decision problems (out of forty) in Part 1, her payoffs in two decision problems she answered in Part 2, the outcome of the Becker et al. (1964) (BDM) mechanism in Part 2, and the participation fee of \$7. The payoffs in the experiment were converted to US dollars at the conversion rate of 10 ECU = 1 USD. Cash payments were made at the conclusion of the experiment in private. The average payments were \$27.90 (including a \$7 participation fee).

Each decision problem in the experiment asked the subjects to choose from five available options and each option had five relevant attributes. Each attribute of an option was an integer from $\{1,2,...,9\}$ and it could be negative or positive. The value of an option for a subject was the sum of its attributes. The subjects knew that their payoff from a decision problem would be the value of their chosen option if that decision problem was selected for payment at the end of the experiment. Figure 1 provides an example of both an available option and an unavailable option presented to the subjects (see Appendix A for examples of the decision screen presented to subjects in each decision problem). Note that the header of each column indicates whether an attribute enters to the option value as a positive or negative integer (plus or minus sign). Whether a column should be added, subtracted, or ignored when calculating the value of an option was only indicated in this header row, so this information had to be continually referenced as the subject considered options at lower positions on the screen. In some decision problems, some of the attributes did not enter the value of an option and those were indicated by zero at the header.[6]

This choice environment takes the tradeoff between attributes in many real-world choice situations as given and extends this to a well-defined and simplified laboratory setting. Recall the health insurance choice example that we introduced in the Introduction. It is commonplace for a consumer to, for example, ask herself "how much higher a premium am I willing to pay for a plan that includes coverage for acupuncture," thereby explicitly weighing the substitution between the coverage for acupuncture and savings on premium. Our experimental environment captures this aspect of valued information using simple weights of 1 and -1 in a linear (perfect substitute) aggregation rule (for attributes that have utility and disutility, respectively) and therefore closely resembles the design of Gabaix et al. (2006) and Caplin et al. (2011).[7]

In the same setting, there are also likely attributes for which a consumer can see information which are not valued. For example, a consumer who always purchases generic drugs will not care about the coverage for branded prescription drugs or a brand-unconscious consumer might say "I dont care whether my health insurance provider is BlueCross or Kaiser Permanente, so I should ignore that information." While she sees the information on brand prescription coverage or insurance provider (as it is displayed invariably with any plan description) on a plan, she will optimally ignore that displayed information, treating it as irrelevant to her current decision. This is captured in our

[6]Our design of varying irrelevant information in two dimensions will later be shown to create symmetric difficulty for subjects. Even though one may think that the perceptual operations required to solve a task are very different in these two dimensions (keeping track of payoffs horizontally and vertically), the impact of these two dimensions on optimality of choice turn out to be similar.

[7]Note that our design differs slightly from Gabaix et al. (2006) and Caplin et al. (2011). In each of those experiments, the coefficient applied to an attribute appeared directly next to the attribute value. To port that design directly to address our research question, we would then have to display zeros for irrelevant attributes as cells in the matrix. In our view, this limits the applicability to real-world scenarios in which we think that information may be irrelevant, even subjectively. We are interested in an environment where irrelevant information is *displayed*, but not *valued*. Furthermore, by including coefficients in the column header only, we treat irrelevant attributes and unavailable options symmetrically, a necessary design component in order to interpret our findings with sufficient generalizability.

experiment by using coefficients of 0 in the header for so-called “irrelevant attributes” (information that has no utility consequence and should be ignored). Additionally, the same consumer might see information for plans for which she is not eligible due to her position in the company. These “unavailable options” should also then be ignored. As it so happens, our decision screens closely resemble the United States Office of Personnel Management Federal Employee Health Benefit plan comparison tool, where employees see a grid of coverage and cost related attributes (some irrelevant) for various plans (some unavailable based on employee status).[8]

In Figure 1, there are ten attributes with a zero in the header and this means that the option had ten irrelevant attributes which did not affect the value of the option for the subjects. In a given decision problem, there were either five relevant attributes (each one with either positive or negative integer value from $\{1, 2, \ldots, 9\}$) or fifteen attributes where five of them were relevant and ten of them were irrelevant. The value of an option was the sum of its positive and negative attributes and it was a randomly generated positive number to guarantee that the subjects will not lose money by choosing an option.

Figure 1: Options with 5 Relevant and 10 Irrelevant Attributes

		+	+	0	0	0	+	0	0	0	0	+	0	0	-	0
☐	Option 1	three	four	three	one	seven	four	four	two	six	two	eight	five	two	six	one
	Option 2	one	eight	two	six	one	five	nine	two	six	two	eight	three	one	seven	nine

Regardless of the type of decision problem, the matrix of information presented to the subject took up the entire screen. This design was chosen to abstract away from possible confounds that lie in the *way* that information is presented. No matter which type of decision problem the subject faced, their eyes were forced to scan the entirety of the screen in order to fully process all relevant information. In this way we abstract away from the possibility that subjects are more capable of processing less (or more) visual space on a computer screen. We chose to add ten unavailable options and/or irrelevant attributes in problems with irrelevant information in part due to screen size limitations; adding any additional options/attributes would introduce the need for scrolling, text size variation across decision problems, and possibly other changes that would introduce confounds to our design. We conjectured that having twice as much irrelevant information than the relevant information in each dimension is sizable.

[8]OPM plan comparison tool: `https://www.opm.gov/healthcare-insurance/healthcare/plan-information/compare-plans/`

In each decision problem, the subjects needed to choose one of the five available options in 75 seconds.[9] In some decision problems they were presented fifteen options and told that only five of them were available to choose from. The other ten were shown on their screens but the subjects were not allowed to choose any of those. O_iA_j is the notation for a decision problem with i options and j attributes. The decision problems that were used in the experiment had $i, j \in \{5, 15\}$; in each case the effective numbers of options and attributes were five, i.e. if the number of options or attributes on a screen was fifteen, then ten of those were either unavailable options or irrelevant (zero) attributes.[10]. Each subject saw the same set of 40 decision problems, differing only in the order in which they were encountered.[11] The order of the decision problems were randomized at the session-individual level (i.e. Subject 1, for instance, in each session, saw the same order of decision problems; with 16 subjects per session, we therefore have 16 distinct decision problem orderings).

Once Part 1 of the experiment was completed, subjects received instructions for Part 2. The aim of Part 2 was to elicit subjects' willingness to pay to eliminate unavailable options or irrelevant attributes to estimate the cost of ignoring irrelevant information. A BDM mechanism was used to measure subjects willingness to pay to remove irrelevant information in one direction. Hence, we elicited the subjects' WTP in four different directions: moving from i) $O_{15}A_5 \to O_5A_5$, ii) $O_5A_{15} \to O_5A_5$, iii) $O_{15}A_{15} \to O_5A_{15}$, and iv) $O_{15}A_{15} \to O_{15}A_5$.[12] The distribution of selling prices used in the BDM procedure (and explained to subjects) was uniform from 0 to 15 ECU. These four BDM elicitation procedures were conducted across two treatments for Part 2 of our experiment: a "Low Noise" treatment and a "High Noise" treatment. Seven sessions were conducted for each treatment. In the Low Noise treatment, BDM procedures were run for (i) and (ii) - WTP was elicited for removal of options or attributes, *given that irrelevant information in the opposite dimension was not present.* In "high noise" treatments, BDM procedures were run for (iii) and (iv) - WTP was elicited for removal of options or attributes, *given that irrelevant information in the opposite dimension was present and cannot be eliminated.* Hence, we elicited the cost of ignoring 10 unavailable options and cost of ignoring 10 irrelevant attributes separately and in two

[9] Subjects earned a payoff of \$0 if they didn't make a choice within 75 seconds.

[10] We also conducted some control experiments for $i, j \in \{5, 8\}$ where we added three (rather than ten) unavailable options or irrelevant attributes to decision problems. Results for those experiments are in Section 4 and Appendices D.1 and D.2

[11] The complete set of decision problems is available as an online Appendix.

[12] Two additional sessions were conducted for robustness wherein we asked for WTP for $O_{15}A_{15} \to O_5A_5$. These results are explained in Section 4 and included in Appendix D.3.

different informational environments. Note that a given subject completed two BDM procedures, with roughly half of our subjects completing (i) and (ii) and half of them completing (iii) and (iv). We chose this between-subject design to eliminate a possible framing effect where a subject may have thought that she was expected to price the elimination of unavailable options or irrelevant alternatives differently depending on the amount of information in the other dimension. Table 1 summarizes the treatments of the experiment.

Table 1: Treatment Summary

Treatment	# of Sessions	# of Subjects	Part 1: Decisions	Part 2: BDM
Low Noise	7	112	40 Decisions	$O_{15}A_5 \to O_5A_5$ and $O_5A_{15} \to O_5A_5$
High Noise	7	110	40 Decisions	$O_{15}A_{15} \to O_5A_{15}$ and $O_{15}A_{15} \to O_{15}A_5$

Subjects completed Parts 1 and 2 without being provided any feedback on their performance in earlier decision problems similar to the experiments in related literature. First, we did not provide feedback after each decision problem in Part 1 in order to avoid any reference dependence or triggering new emotions such as regret. For example, a subject may work harder than she otherwise would if she knows that she would receive feedback on how suboptimal her decision was. Second, we do not provide aggregate feedback at the end of Part 1 to avoid unnecessary priming and to more closely approximate an analogous real-world setting. Direct feedback regarding mistake rates and/or time spent in each decision problem type may induce the subject to think that they should be willing to pay to eliminate irrelevant information, even if the subject does not intrinsically possess such a preference. We view the potential effect of feedback in this setting as analogous to an experimenter demand effect.

After the completion of Parts 1 and 2, the subjects answered a demographic questionnaire where they reported gender, age, college major, self-reported GPA, SAT, and ACT scores, and they were given the chance to explain their decisions in Part 2 of the experiment.

3 Experimental Results

Our main hypothesis is that unavailable options and irrelevant attributes cause cognitive overload for the decision makers and this leads to sub-optimal choice. In the following analysis, we say that a "mistake" has been made in an individual decision problem when the subject failed to select the highest valued available option presented within the time limit of 75 seconds. If no option was chosen, this is coded as a "timeout."

3.1 Part 1: Decision Task

In this section we present the results from Part 1 of the experiment. We begin with aggregate results and then re-investigate these results by controlling for decision problem characteristics and demographic controls.

3.1.1 Aggregate Results

Table 2 presents the mistake rate for each type of decision problem O_iA_j in the aggregate data for $i, j \in \{5, 15\}$, treating timeouts as mistakes, calculating the "mistake rate" for each treatment as the average of subject-level mistake rate. Note that the addition of unavailable options and irrelevant attributes alone does not generate significantly larger mistake rates relative to the benchmark O_5A_5 (p-values 0.584 and 0.653, respectively for decision problem types $O_{15}A_5$ and O_5A_{15}). However, conditional on the presence of either unavailable options or irrelevant attributes (in types $O_{15}A_5$ and O_5A_{15}), the addition of irrelevant information in the opposite dimension does increase mistake rates by about 50% (p-value 0.000 in each case). Thus, in the aggregate, the interaction between unavailable options and irrelevant attributes generates increased mistake rates. We believe that this is evidence that our design does not favor one type of irrelevant information over the other. If, for some reason, our design explicitly allowed for easier processing of either unavailable options or irrelevant attributes, we'd expect to see that mistake rates would respond to an increase in irrelevant information in only one dimension. This is clearly not the case. As such, we would expect our mistake rate results to be robust to permutations of our design, for example, where the matrix of displayed data was transposed. The results are qualitatively similar when we do not count timeouts as mistake. These results can be found in Table 17 in Appendix B.1.

Table 2: Mistake Rates: Timeouts as Mistakes

		O_5	O_{15}
A_5	Mean	0.213	0.218
	Std Error	0.013	0.013
	N	222	222
A_{15}	Mean	0.228	0.337
	Std Error	0.012	0.016
	N	222	222

$p = 0.000$ for $O_{15}A_5 \rightarrow O_{15}A_{15}$, $O_5A_{15} \rightarrow O_{15}A_{15}$, and $O_5A_5 \rightarrow O_{15}A_{15}$
$p > 0.100$ otherwise.

Note that when a subject finds a decision problem more challenging, she may react to this in two ways: (i) she may take more time to make decision and this may or may not lead to an optimal choice; (ii) she may run out of time and computer may record this as a sub-optimal choice. Even though the mistake rates in Table 2 do not change much when only the number of options is increased while the number of attributes are kept at 5 (from O_5A_5 to $O_{15}A_5$) and when only the number of attributes is increased while the number of options are kept at 5 (from O_5A_5 to O_5A_{15}), this does not necessarily mean that the subjects find the increased number of options or attributes in only one dimension not challenging. This increase in the difficulty of the decision problem may also appear as increased time required to submit a decision. Table 3 reports on the average time (in seconds) at which subjects submit a decision in each type of decision problem. Observations where the subject did not submit a decision in the allotted time were are excluded in Table 3. For results that treat timeouts as the maximum time allotted (i.e. $time = 75$) and for the sub-sample where the subject chose the correct (optimal) option, see Tables 18 and 19 in Appendix B.1, respectively; results are not qualitatively different from those presented in Table 3.[13]

Note that adding irrelevant information in any dimension (i.e. unavailable options or irrelevant attributes) increases the time spent on each decision problem in Table 3. However, this difference is not statistically significant when moving from O_5A_5 to $O_{15}A_5$. Time costs increase much more

[13]An interested reader may wonder whether our central results are dependent on the specific time limit chosen in our design. First, note that in Table 19, the mean time taken to choose correctly is substantially less than the time limit of 75 seconds for each type of decision problem. We take this as evidence that our time limit was not meaningfully binding for a very large portion of our subject pool. Additionally, we conducted four pilot sessions under various design schemes, all without any time limit. Results, including mistake rates and time spent per problem, are qualitatively similar and are available upon request.

substantially when irrelevant information in one dimension is already present. For example, the time spent increases by just over one second on average with the addition of unavailable options when there are no irrelevant attributes displayed (in the first row of Table 3), but increases by nearly 4 seconds when there are irrelevant attributes displayed (in the second row of Table 3). A similar effect is present for the addition of irrelevant attributes. Furthermore, from Table 3 we may surmise that irrelevant attributes increase time spent more than unavailable options: time spent increases more on average when moving vertically down in Table 3 than when we move horizontally across it. Both these interaction and asymmetry effects will be investigated further in the next subsection.

Table 3: Time: No Timeouts

		O_5	O_{15}
	Mean	48.605	49.926
A_5	Std Error	0.712	0.680
	N	222	222
	Mean	52.935	56.365
A_{15}	Std Error	0.780	0.810
	N	222	222

p = 0.00 for $O_5A_5 \to O_5A_{15}$, $O_{15}A_5 \to O_{15}A_{15}$,
$O_5A_{15} \to O_{15}A_{15}$, $O_5A_5 \to O_{15}A_{15}$, and $O_{15}A_5 \to O_5A_{15}$
$p > 0.10$ for $O_5A_5 \to O_{15}A_5$

Finally, given that there is a time limit of 75 seconds for each decision problem, the increased difficulty that could arise from the presentation of irrelevant information could also increase the rate at which timeouts occur in each type of decision problem. Recall that subjects earn zero in the case of a timeout and letting 75 seconds pass without a choice is worse than choosing randomly. Timeouts are not prevalent in our data: only 4.67% of decision problems resulted in a timeout. 60.31% of timeouts occurred within the first ten periods; 31.16% occurred in the first period. Further, note that our choice of a time threshold is somewhat arbitrary: we could have easily chosen to give subjects more (or less) time to complete each decision problem. As such, we ignore timeouts as a significant concern for the remainder of our analysis, conducting all tests conditional on experiencing no timeouts.[14]

From all of the above, we are left with the following main aggregate results: i) irrelevant attributes and unavailable options are both necessary to generate increased mistake rates within the parameter range used in our experiments, and ii) time costs are increased by irrelevant information displayed in either dimension. We summarize these findings in Result 1. In order to investigate each of these in more detail, we conduct regression analysis to control for individual-level heterogeneity and learning in the following subsection.

Result 1 *Decision makers cannot always freely dispose of irrelevant information.*

- *Unavailable options and irrelevant attributes can affect mistake rates. The interaction between the two amplifies this effect.*[15]
- *Both unavailable options and irrelevant attributes independently generate increased time costs.*

3.1.2 Decision Problem Characteristics and Demographic Controls

To further investigate the effects of irrelevant information on the mistake rate, we conduct logistic regressions controlling for learning, gender, and academic achievement effects. Table 4 reports regression results where the dependent variable is "Mistake" and the independent variables are varied in different models specified. "Mistake" is a binary variable with 1 corresponding to the subject failing to select the element with the maximal value in the set of (available) alternatives. It is equal to 0 otherwise. In all models, the independent variables are as follows: "Options" is a dummy variable indicating the presence of 10 additional unavailable options displayed (i.e. Options is equal to 1 for type $O_{15}A_5$ and $O_{15}A_{15}$ decision problems and it is 0 otherwise), "Attributes" is defined analogously for irrelevant attributes (i.e. Attributes = 1 for type O_5A_{15} and $O_{15}A_{15}$ decision problems), "Options * Attributes" is the interaction between the type dummies, "Female" is a dummy variable indicating whether the subject is female, "English" is a dummy variable indicating whether the subject's native language is English, "Economics/Business" is a dummy variable

[14] There were four subjects who experienced timeouts in more than 20% of their decision problems. They are included in the sample upon which all analysis is conducted, but results are not qualitatively different if they are excluded.

[15] Additional results using alternative parameters that are discussed in Section 4 and Appendix D show that this finding is not driven solely by the increase in the amount in irrelevant information displayed; instead caused by the introduction of both unavailable options and irrelevant attributes).

indicated whether the subject's major is in the University of Maryland Economics Department or Business School, "Period" is the period in which the decision problem was presented, and "Period^2" is its square. Reported coefficients are calculated marginal effects. Standard errors are clustered at the Subject level.

Cognitive Scores were calculated using a combination of responses on the Demographic Questionnaire. Responses for GPA, SAT, and ACT were normalized as in Cohen et al. (1999) and Filiz-Ozbay et al. (2016): Let j be the variable under consideration with $j \in \{\text{GPA, SAT, ACT}\}$, μ_i^j be the value of variable j for subject i, μ_{max}^j be the maximum value of j in the subject population, and μ_{min}^j be the minimum value of j in the subject population. Then let $\hat{\mu}_i^j$, the normalized value of variable j for subject i, be defined as follows:

$$\hat{\mu}_i^j = \frac{\mu_i^j - \mu_{min}^j}{\mu_{max}^j - \mu_{min}^j}$$

such that $\hat{\mu}_i^j$ can be interpreted as the measure of j for subject i, normalized by the distribution of j in the subject population. Some subjects were missing one or more measures for $j \in \{\text{GPA, SAT, ACT}\}$, since these measures were self-reported (and some subjects could not recall their scores on one or more of these measures). As such, the Cognitive Score for subject i was set to $\hat{\mu}_i^{GPA}$ if the subject reported a feasible GPA, $\hat{\mu}_i^{SAT}$ if a feasible GPA score was missing and the subject reported a feasible SAT score, and $\hat{\mu}_i^{ACT}$ if feasible GPA and SAT scores were both missing and the subject reported a feasible ACT score. GPA Scores were given precedent in the calculation of Cognitive Scores because most subjects could reliably report these while SAT Scores took precedent over ACT Scores because it is more common for University of Maryland, College Park undergraduates to have taken the SAT. Results based on using GPA only are presented in Appendix B.3 and are qualitatively similar.

In addition to the above specified independent variables, we include two more variables in all models: "Position" and "Positive". The variable "Position" is simply the position, from 1 to 15, of the optimal available option that is displayed. Previous work, including Caplin et al. (2011), has shown that subjects often search a list from top to bottom, implying that optimal options displayed lower-down on the list have a lower probability of being chosen due to the early termination of search. We thus include this variable as a control in each of our model specifications, its coefficient being significant and positive in all instances: subjects make more mistakes and spend more time when the optimal option is presented further down a list of alternatives. The variable "Positive" is the number of positive relevant attributes displayed in the decision problem, ranging from three to five.[16] There are potentially two reasons why "Positive" would matter in a given decision problem: i) a subject responds with increased effort in the presence of stronger incentives and ii) subjects find the task less difficult with fewer subtraction operations. The first comes from the fact that, given our data generation process, the expected value of the optimal available option is increasing in the number of positive attributes. Subjects may then work harder or stop search later in the presence of five positive attributes than in the presence of, say, three positive attributes. It also may be that subtraction operations are more difficult cognitively than addition operations such that the difficulty of the task is decreasing in the number of positive attributes. In Table 4, the coefficient on Positive is negative in all relevant model specifications: more addition operations decreases the incidence of mistakes. Clearly this is consistent with both increased effort provision and decreased cognitive difficulty of the task. However, the coefficient on Positive is also negative in all relevant models in Table 7, indicating that subjects spend less time in the presence of more addition operations. Combined, these results are consistent with addition operations being easier in terms of cognitive load.

Finally, any effects of irrelevant information that we may find could possibly be due simply to the increased *complexity* of the decision problem when irrelevant information is added, not due to the mere *presence* of irrelevant information. For example, adding unavailable options to a decision problem forces the DM to have to "skip" more visual information on the screen in order to evaluate an individual available option, since whether an attribute is positive or negative is displayed at the top of the screen. Similarly, irrelevant attributes force the DM to interrupt the evaluation process, visually "skip" a column of irrelevant information, and then continue with evaluation. Therefore, we define "Attribute Complexity" and "Option Complexity" as the number of "skips" required for full search/evaluation in the decision problem. For example, Option 1 in the example Figure 1 above, has a "Attribute Complexity" equal to 3 (since there are essentially three groups

[16] Our data generation process gave equal weight to the possibility of having a positive or negative relevant attribute. However, we only used generated decision problems that i) had a unique optimal available option and ii) had all positive-valued available options. Thus, the range of the number of positive available options in the generated dataset is more restrictive than that which would be generated without these constraints.

of irrelevant attributes encountered for full evaluation of the option). In the baseline O_5A_5 decision problems, both of these variables are set equal to 0. In the regressions reported in Tables 4 and 7, when "Options"("Attributes") is equal to 1, "Option Complexity" ("Attribute Complexity") varies between 2 and 5 in the realized data.[17]

The regressions in Table 4 are conducted on the sub-sample where the submission is made in under 75 seconds. As mentioned above, specifications that treat timeouts as mistakes or not are qualitatively similar (see Models 4 and 5 in Table 4). In Model 1, we replicate the aggregate result that can be seen in Table 2: unavailable options and irrelevant attributes increase the mistake rate when presented jointly. Having irrelevant information in both of these dimensions increases the mistake rate by up to 9.9 percentage points (in Model 5). Moreover, this effect is not due to the "complexity" of the decision problem in the presence of irrelevant information, as both Attribute Complexity and Option Complexity are insignificant in Model 4.

In order to investigate whether this main result is robust to specifications of welfare loss other than the mistake rate, we conducted analyses using two additional welfare measures: Normalized Monetary Loss and the Rank of the final choice. These results are displayed in Tables 5 and 6, respectively, and the results are qualitatively similar to those found in Table 4 for the mistake rate.

Because of differences in option values across decision problem treatments as a result of the data generation process, we used the following normalization for this loss measurement in Table 5: we take the actual loss for the choice of the subject (i.e. the difference between the Maximum Option Value in Decision Problem and the Value of Choice) and divide it by the difference between the Maximum Option Value and the Mean Value of available options in the decision problem. The variable Rank used in Table 6 runs from 1, indicating that the worst available option is chosen, to 5, indicating that the best available option is chosen. In some decision problems, several available options (other than the best) had the same monetary value. For these observations, the midpoint of the relevant Rank was used (e.g. if the 2nd and 3rd best available options were of the same monetary value, they were both recorded as Rank of 2.5).[18] We see that the qualitative message of these regressions is similar to our mistake rate analysis: subjects take on more normalized monetary loss and choose lower ranked options when both unavailable Options and irrelevant Attributes are

[17]We further explore alternative complexity measures for relevant subsamples of this dataset in Appendix B.4.

[18]Our results are robust to i) dropping all observations with such a "tie" and iii) rounding up such "ties" and these results are available upon request.

Table 4: Mistake Rate Regressions

	(1) Mistake	(2) Mistake	(3) Mistake	(4) Mistake	(5) Mistake †
Options	0.010	0.010	-0.023*	-0.049*	-0.061**
	(0.011)	(0.011)	(0.013)	(0.028)	(0.029)
Attributes	-0.000	0.000	-0.007	-0.011	0.017
	(0.012)	(0.012)	(0.012)	(0.028)	(0.028)
Options * Attributes	0.086***	0.086***	0.093***	0.094***	0.099***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Period	-0.007***	-0.007***	-0.007***	-0.007***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Period^2	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive Score		-0.217***	-0.218***	-0.218***	-0.224***
		(0.063)	(0.063)	(0.063)	(0.063)
Female		0.077***	0.077***	0.077***	0.078***
		(0.021)	(0.021)	(0.021)	(0.021)
Economics/Business		-0.008	-0.008	-0.008	0.003
		(0.025)	(0.025)	(0.025)	(0.026)
English		-0.003	-0.003	-0.003	-0.013
		(0.022)	(0.022)	(0.022)	(0.023)
Position			0.005***	0.005***	0.006***
			(0.001)	(0.001)	(0.001)
Positive			-0.030***	-0.031***	-0.031***
			(0.008)	(0.008)	(0.008)
Attribute Complexity				0.001	-0.002
				(0.007)	(0.007)
Option Complexity				0.007	0.009
				(0.007)	(0.007)
Observations	8555	8555	8555	8555	8880
Session FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Each Model: 222

†: Timeouts treated as mistakes

Marginal effects from logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

present. In Tables 4, 5, and 6, the coefficients of Period and Period^2 indicate that Period's effect on suboptimal choice has a U-shape (coefficients on Period and Period^2 are significant and negative and positive, respectively, in Tables 4 and 5 and the reverse in Table 6). Hence, the overall effect of learning would not undo our main result, had we only included more Periods and decision problems.[19]

Table 5: Normalized Loss Regressions

	(1) Loss	(2) Loss	(3) Loss	(4) Loss
Options	0.114**	0.113**	-0.078	-0.183
	(0.050)	(0.050)	(0.054)	(0.117)
Attributes	0.063	0.066	0.021	0.010
	(0.051)	(0.051)	(0.051)	(0.116)
Options * Attributes	0.248***	0.245***	0.293***	0.297***
	(0.077)	(0.077)	(0.077)	(0.077)
Period	-0.026***	-0.027***	-0.030***	-0.029***
	(0.007)	(0.007)	(0.007)	(0.007)
Period^2	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive Score		-0.978***	-0.975***	-0.976***
		(0.276)	(0.275)	(0.275)
Female		0.340***	0.339***	0.339***
		(0.097)	(0.096)	(0.096)
Economics/Business		-0.042	-0.042	-0.041
		(0.114)	(0.114)	(0.114)
English		0.014	0.009	0.010
		(0.099)	(0.099)	(0.099)
Position			0.024***	0.026***
			(0.005)	(0.005)
Positive			-0.201***	-0.207***
			(0.034)	(0.034)
Attribute Complexity				0.003
				(0.031)
Option Complexity				0.029
				(0.030)
Observations	8555	8555	8555	8555
Session FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
Number of Subjects in Each Model: 222
Tobit regresions specifications with lower limit = 0, upper limit = 3.5
Robust standard errors reported are clustered at the Subject level
$^* p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$

[19] See Table 27 and Figure 3 in Appendix C for learning trends across decision problem types.

Table 6: Rank Regressions

	(1) Rank	(2) Rank	(3) Rank	(4) Rank
Options	-0.215*	-0.211*	0.185	0.363
	(0.112)	(0.113)	(0.124)	(0.274)
Attributes	-0.079	-0.087	0.004	0.244
	(0.114)	(0.114)	(0.114)	(0.264)
Options * Attributes	-0.664***	-0.660***	-0.756***	-0.761***
	(0.171)	(0.172)	(0.171)	(0.172)
Period	0.064***	0.064***	0.071***	0.070***
	(0.016)	(0.015)	(0.015)	(0.015)
Period^2	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive Score		2.206***	2.203***	2.206***
		(0.620)	(0.619)	(0.619)
Female		-0.746***	-0.745***	-0.744***
		(0.218)	(0.217)	(0.217)
Economics/Business		0.084	0.083	0.083
		(0.260)	(0.260)	(0.260)
English		-0.002	0.007	0.008
		(0.226)	(0.226)	(0.226)
Position			-0.051***	-0.052***
			(0.011)	(0.012)
Positive			0.401***	0.408***
			(0.079)	(0.080)
Attribute Complexity				-0.070
				(0.071)
Option Complexity				-0.052
				(0.069)
Observations	8555	8555	8555	8555
Session FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Each Model: 222

Tobit regression specifications with lower limit = 1, upper limit = 5

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In order to investigate the heterogeneity in time responses to these different types of decisions problems, we present the results of several random-effect Tobit regression models in Table 7. Observations are censored below by 0 and above by 75 seconds.[20] In each model presented the dependent variable is Time (measured in seconds), defined as the time at which the subject submits her decision. As in previous model specifications, Models 1 - 4 are conducted on the sub-sample where the time of submission is less than 75 seconds (i.e. excluding timeouts and submissions in the last second). All variables are defined as previously mentioned. In Model 1, we present the simplest model incorporating the effects of the presence of irrelevant information on the time to reach a decision. We find results that are similar to those seen in Table 3: irrelevant information displayed in either dimension increases time costs considerably. Further, we confirm that there are interaction effects: that having both unavailable options and irrelevant attributes increases time spent by between 1.729 seconds (in Model 2) and 3.481 seconds (in Model 5) above the individual decision problem type effects. We also discover that irrelevant information has an asymmetric effect on time spent depending on the dimension: irrelevant attributes increase time costs more than unavailable options ($\beta_{Attributes} > \beta_{Options}$; $p - value = 0.000$). Finally, from Model 4 it can be seen that the effect of Options on time to make a decision stems from the increased complexity; Option Complexity is positive and significant in Model 4 while the coefficient on Options is insignificant.[21]

We summarize all of the aforementioned results in Result 2:

Result 2 *When controlling for subject-level heterogeneity and learning, we replicate the results found in Result 1. Namely, that subjects cannot always freely dispose of irrelevant information.*

A comparison of the results on the mistake rate and time spent can potentially illuminate some of the mechanisms involved in decision making in this experiment. For example, we see that both Options and Attributes increase Time spent in a decision problem, but not the Mistake rate. Further, consider the fact that the average number of seconds spent in an O_5A_5 decision problem is approximately 48.6 seconds (seen in Table 3), indicating that with no irrelevant information, subjects have "time to spare" on average. With the addition of irrelevant information in either

[20] To investigate the sensitivity of our results to this choice, we conduct further regressions using lower time thresholds. These can be found in Tables 20 and 21 of Appendix B.2.

[21] Across all model specifications, we find some evidence of learning and subject-level heterogeneity, including gender, native language, and cognitive ability effects. However, our experiment was not explicitly designed to test for the effects of these demographic variables. As such, these results are included as statistical controls.

Table 7: Time Regressions

	(1) Time	(2) Time	(3) Time	(4) Time	(5) Time†	(6) Time‡
Options	2.215***	2.217***	1.136**	-1.669*	-1.121	-1.470
	(0.381)	(0.380)	(0.465)	(0.949)	(0.965)	(0.906)
Attributes	5.655***	5.649***	5.367***	4.922***	5.083***	4.629***
	(0.430)	(0.430)	(0.438)	(0.932)	(1.084)	(0.885)
Options * Attributes	1.734***	1.729***	1.991***	2.112***	3.481***	1.956***
	(0.499)	(0.499)	(0.500)	(0.503)	(0.532)	(0.486)
Period	-0.394***	-0.395***	-0.412***	-0.403***	-0.190***	-0.350***
	(0.078)	(0.078)	(0.079)	(0.079)	(0.067)	(0.074)
Period^2	0.002	0.002	0.003	0.003	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cognitive Score		9.054**	9.052**	9.053**	6.520**	9.141**
		(4.251)	(4.251)	(4.252)	(3.277)	(4.158)
Female		-2.377*	-2.378*	-2.378*	-1.540	-2.398*
		(1.354)	(1.354)	(1.354)	(1.124)	(1.325)
Economics/Business		-1.739	-1.740	-1.741	-2.620*	-1.860
		(1.601)	(1.601)	(1.601)	(1.378)	(1.563)
English		-3.451**	-3.452**	-3.452**	-2.076	-3.295**
		(1.496)	(1.496)	(1.496)	(1.357)	(1.462)
Position			0.146***	0.184***	0.191***	0.172***
			(0.040)	(0.042)	(0.045)	(0.041)
Positive			-1.257***	-1.443***	-1.068***	-1.430***
			(0.274)	(0.279)	(0.275)	(0.269)
Attribute Complexity				0.118	-0.031	0.148
				(0.228)	(0.292)	(0.215)
Option Complexity				0.774***	0.588**	0.727***
				(0.223)	(0.233)	(0.211)
Observations	8880	8880	8880	8880	6668	8880
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Each Model: 222

†: Conditional on Correct

‡: Timeouts treated as Time = 75 seconds

Marginal effects reported from tobit regressions censored below by 0 and above by 75

Robust standard errors are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

direction alone, subjects might then spend more time (as indicated in Table 7), but that the additional time required to find the best option in the presence of irrelevant information might not push the subject over the 75 second time limit. The evidence in Tables 4 and 7 are suggestive of such a mechanism. Furthermore, note that Option Complexity significantly increases Time spent in the decision problem, but not the mistake rate (see models 4 - 6 in Table 7 and models 4 - 5 in Table 4, respectively). This would also indicate that in the presence of increased decision problem complexity, subjects spend additional time, but that this additional time spent does not cause the time constraint to be binding and hence, does not make the subject more likely to choose sub-optimally due to the increased complexity.

A comparison of these results suggests that it is worthwhile to investigate the effects of Time spent in a decision problem on the Mistake Rate. Table 8 displays results from logistic regressions used to explicitly test for the effect of additional time spent in the decision problem on the mistake rate and how this effect differs by decision problem type. Model 1 is conducted for the sub-sample excluding decision problems of type $O_{15}A_{15}$ and shows that increased time spent does not decrease the mistake rate. Model 2 is conducted for the sub-sample excluding decision problems of type O_5A_5 and shows that increased time spent does decrease the mistake rate in the presence of additional irrelevant information so long as irrelevant information was already present. For example, the coefficient on Time * Attributes in model 2 tells us that an additional second spent in a decision problem of type $O_{15}A_{15}$ reduces the mistake rate by 0.3 percentage points relative to an additional second spent in $O_{15}A_5$. In each model, we test whether the coefficients on Time * Attributes and Time * Options are different from one another and fail to reject the null in each instance ($p > 0.1$ in both tests), indicating that additional Options and Attributes have symmetric effects on the effectiveness of time on the mistake rate.

Taken together, the results in Table 3 and Table 8 illuminate a possible mechanism through which we see our results. In general, subjects do spend more time on decision problems with irrelevant information. This additional time spent does not, however, "pay off" by decreasing the mistake rate when irrelevant information is presented in only one dimension. However, conditional on irrelevant information being present in both dimensions, additional time spent does decrease the mistake rate, though not enough to undo the direct effect of the irrelevant information on the mistake rate, as evidenced by our results in Tables 2 and 4.

Table 8: Effect of Time Spent on Mistake Rate

	(1) Mistake	(2) Mistake
Options	0.003	0.171***
	(0.050)	(0.053)
Attributes	0.062	0.241***
	(0.052)	(0.056)
Period	-0.007***	-0.006***
	(0.002)	(0.002)
Period^2	0.0002***	0.0001***
	(0.000)	(0.000)
Time	-0.001	0.002
	(0.001)	(0.001)
Time * Attributes	-0.000	-0.003***
	(0.001)	(0.001)
Time * Options	-0.000	-0.002***
	(0.001)	(0.001)
Position	0.004***	0.006***
	(0.002)	(0.001)
Positive	-0.040***	-0.035***
	(0.009)	(0.009)
Attribute Complexity	-0.014	0.003
	(0.010)	(0.008)
Option Complexity	-0.006	0.011
	(0.009)	(0.007)
Observations	6460	6393
Session FE	Yes	Yes
Demographics	Yes	Yes
Sample	$\mathrm{O}_5 A_5, O_5 A_{15}, O_{15} A_5$	$\mathrm{O}_5 A_{15}, O_{15} A_5, O_{15} A_{15}$

Standard errors in parentheses
Number of Subjects in Each Model: 222
Marginal effects from logit regression specifications
Robust standard errors reported are clustered at the Subject level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Part 2: Willingness-To-Pay

Recall that the second part of the experiment elicited subjects WTP to eliminate unavailable options and irrelevant attributes in both "Low Noise" and "High Noise" environment. For reference, recall that the support of the BDM procedure used was $[0, 15]$ Experimental Currency Units (ECUs) with a uniform distribution. We have some observed variation in WTP data. By just looking at this CDF of submitted WTP amounts, Figure 2 reports that subjects are smoothly distributed in the support of the BDM range we provided. Such a smooth distribution is also observed when we look at the WTP data for Low and High Noise environments separately.

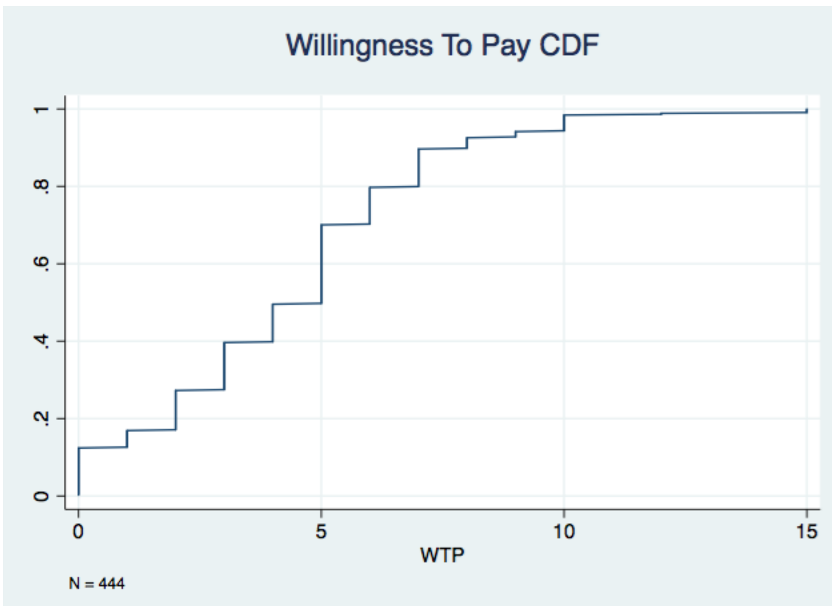


Figure 2: CDF of WTP

Table 9 shows the average WTP, measured in ECUs, for each type of elimination. Table 9 can be read from left to right as "WTP to eliminate Attributes given that there are only 5 Options", "WTP to eliminate Options given that there are only 5 Attributes", etc. The first two columns belong to our "Low Noise" treatment and the last two belong to our "High Noise" treatment. Note that subjects participated in only one of these treatments; a given subject submitted her WTP for either columns 1 and 2 or columns 3 and 4. Thus, when making comparisons between WTP within a particular information treatment (Low or High), we match the data by subject. Let WTP to get rid of information be written as follows: $WTP(X|Y_n)$ where X is the dimension of information they are paying to remove given Y-dimension information with n units. For example, $WTP(A|O_5)$ is the

WTP to eliminate 10 irrelevant Attributes, given that five options are present (all of them available). WTP to reduce attributes is significantly higher than WTP to reduce options only in the low noise case. (p-value = 0.021 in Wilcoxon Signed-Rank Test with $H_0 : WTP(A \mid O_5) = WTP(O \mid A_5)$).

Tests of whether $WTP(A|O_5)$ is greater (less) than $WTP(A|O_{15})$ and whether $WTP(O|A_5)$ is greater (less) than $WTP(O|A_{15})$ were conducted un-matched as these were submitted independently by separate subjects. There is no significant difference between WTP to get rid of Attributes or Options by "Low Noise" or 'High Noise" treatment. Recall that eliminating irrelevant information in one dimension does not affect mistake rates significantly when there is no irrelevant information in the other dimension. However, eliminating irrelevant information in one dimension does affect the mistake rate when there is irrelevant information in both dimensions. Subjects do not seem to anticipate this effect on mistake rates when setting their WTP. Additionally, Table 10 reports the frequency of positive WTP for each treatment. The vast majority of our observations are strictly positive, with no statistical difference between treatments, either matched within subject or across Low Noise and High Noise treatments.

Average WTP for any case in Table 9 is between 4 and 5 ECU. One may question whether this amount is reasonable with respect to the mistakes subjects made in more difficult decision problems. If we compare the average amount of money subjects made in O_5A_5 versus O_5A_{15} and $O_{15}A_5$ and check whether the decrease in average earnings in decision problems with unavailable options or irrelevant attributes is less or more than the WTP in the corresponding decision problem, we may argue that subjects over- or underpaid to simplify their tasks. Such analysis gives us about a 1 - 2 ECU decrease in payoffs with more complicated problems and that is much lower than the observed WTP amounts. We will further explore one reason for such overpayment in Subsection 3.3: a "preference for simplicity."

Table 9: Willingness to Pay

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
Mean	4.473	4.071	4.473	4.373
Std Error	0.286	0.266	0.275	0.273
N	112	112	110	110

$p = 0.021$ for $H_0 : WTP(A|O_5) = WTP(O|A_5)$

$p > 0.100$ otherwise

Table 10: Frequency of Positive WTP

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
Mean	0.893	0.866	0.864	0.882
Std Error	0.029	0.032	0.033	0.031
N	112	112	110	110

$p > 0.100$ in all relevant comparisons

The regressions reported in Table 11 were conducted in order to understand the heterogeneity in the subjects willingness to pay in each of the four directions where irrelevant information could be removed. Table 11 displays results aggregated across the Low Noise and High Noise treatments. Note that in all these regressions, Attributes is a binary variable indicating whether the dependent variable is $WTP(A|O_n)$. When Attributes = 0, the dependent variable is $WTP(O|A_n)$.[22] The variable "High Noise" is a dummy variable used to indicate whether the observation is from a High Noise treatment. All interaction variables used in Table 11 are straightforward.[23]

First we ask if WTP to eliminate irrelevant information in either dimension is sensitive to measures of performance in Part 1 of the experiment, despite there being no feedback provided prior to Part 2. Models 1 - 3 are Tobit regression specifications with a lower limit of 0 and an upper limit of 15 (i.e. the support of the BDM mechanism used in Part 2 of the experiment). Note that in all models, Mistakes and Time are a count of the number of mistakes and the sum of time spent across all decision problems in the treatment under consideration for WTP. For example, if a subject in the low noise WTP treatment made 7 mistakes across the 10 O_5A_{15} decision problems and spent a total of 500 seconds across these same 10 decision problems, Mistakes would equal 7 and Time would equal 500 for the observation of $WTP(A \mid O_5)$ for this subject.

WTP increases with the incidence of mistakes: Mistakes is positive and significant in all models in Table 11. This is somewhat surprising, given that subjects were not provided feedback between Parts 1 and 2 of the experiment; it seems that subjects are aware of a general level of optimality of choice and are thus more willing to pay to eliminate irrelevant information if they make more mistakes in the corresponding decision problem type.

[22] For these regressions, answers submitted at $time = 75$ seconds are coded as mistakes to avoid collinearity of regressors.

[23] Table 24 of Appendix B.3 repeats the regressions reported in Table 11 by replacing the measure for Cognitive Score with self-reported GPA. The results are qualitatively the same.

Additionally, we ask if these performance measures influence *whether* WTP is positive: it is possible that WTP itself is not sensitive to individual measures of performance, but that performance in one dimension can affect whether WTP is positive at all. Models 4 through 6 report coefficients from logistic regression specifications where the dependent variable is a binary variable indicating whether WTP is greater than 0. There is evidence that whether WTP is greater than zero is affected by Mistakes (see Models 4 - 6).

Notably, WTP is not sensitive to increased time spent on decision problems (see coefficient on Time in Models 1 - 6 in Table 11; Time is only marginally significnat in Model 2). Additionally, subjects appear to be more willing to pay to eliminate any irrelevant information in the High Noise treatments rather than the Low Noise treatments (see coefficients on High Noise in Models 1 and 2). This is true only at the intensive margin (i.e. in Models 1 - 2) and is at varying (and marginal) significance levels across these same models. Further note that in Table 9 we showed that WTP was higher for the elimination of Attributes than for the elimination of Options, though only in the Low Noise treatment. This result disappears in Table 11 when we have performance and demographic controls. We think that (lack of) feedback provided to subjects may prevent them from setting consistent WTP in Low Noise and High Noise treatments and between Attributes and Options. Further study on the role of feedback in such environments is necessary. We summarize these results in Result 3:

Result 3 *WTP is heterogeneous and sensitive to a number of independent variables:*

- *WTP increases with the number of mistakes made in the relevant decision problem type*
- *Higher mistake rates increase the likelihood that WTP is strictly positive*

Notice that in Models 1 - 3 of Table 11, the constants are positive, though insignificant. For example, consider a subject for whom irrelevant information has no effect: they never make more mistakes when irrelevant information is present and they never spend more (or less) time. This subject may *still* be willing to pay some amount to eliminate this information. We'll call this a "preference for simplicity" - even in the absence of any effect of irrelevant information on choice, decision makers prefer to exclude it. We investigate this further by analyzing individual WTP for

Table 11: WTP Regressions

	(1) WTP	(2) WTP	(3) WTP	(4) WTP > 0	(5) WTP > 0	(6) WTP > 0
Mistakes	0.413***	0.407***	0.329***	0.379***	0.333***	0.341**
	(0.102)	(0.104)	(0.118)	(0.124)	(0.121)	(0.156)
Time	0.003	0.003*	0.003	0.002	0.002	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Attributes	0.191	0.189	0.312	0.022	0.010	0.205
	(0.156)	(0.155)	(0.276)	(0.159)	(0.158)	(0.301)
High Noise	2.296*	2.557**	1.961	0.793	0.729	1.185
	(1.200)	(1.216)	(2.416)	(1.401)	(1.505)	(2.589)
Female		-0.276	-0.245		0.473	0.467
		(0.440)	(0.433)		(0.487)	(0.475)
Cognitive Score		-0.992	-1.021		-1.355	-1.331
		(1.138)	(1.119)		(1.044)	(1.047)
High Noise * Mistakes			0.152			-0.015
			(0.199)			(0.228)
High Noise * Time			0.001			-0.000
			(0.004)			(0.004)
High Noise * Attributes			-0.237			-0.391
			(0.326)			(0.328)
Constant	0.394	1.076	1.278	-0.038	0.813	0.667
	(1.281)	(1.438)	(1.725)	(1.363)	(1.560)	(1.824)
Observations	444	444	444	386	386	386
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Baseline: 222

29 Subjects dropped from Models 4 - 6 because session FE perfectly predicts WTP > 0

Models 1 - 3: Tobit regression specifications with lower limit of 0 and upper limit of 15

Models 4-6: Logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

those subjects who experience no increase in mistake rates in the presence of irrelevant information in the following subsection.

3.3 A Preference For Simplicity

To more precisely estimate whether and to what extent such a preference for simplicity exists, we look at WTP for two categorizations of subjects for a given decision problem: i) those who experience no additional mistakes and ii) those who make no additional mistakes and incur no time costs associated with the presence of irrelevant information. Our interpretation of "making no additional mistakes" is straightforward: a subject is deemed to have made "no additional mistakes" in decision problems of type O_iA_j if her mistake rate in O_iA_j was weakly less than her mistake rate in O_iA_{j-10} for $j = 15$ (or $O_{i-10}A_j$, for $i = 15$). In other words, a subject is counted in the first row of Tables 12 and 13 if she indeed made no additional mistakes as a result of irrelevant information in the relevant dimension. For example, a subject in the High Noise treatment who made 2 mistakes in $O_{15}A_5$ and 1 mistake in $O_{15}A_{15}$ will be considered to have made "no additional mistakes" in $O_{15}A_{15}$ because her mistakes didn't increase with the addition of irrelevant attributes. In all of the analysis in this section, Timeouts were treated as Mistakes, but results are robust to the exclusion of Timeouts.

We additionally consider subjects who make no additional mistakes *and* incur no additional time costs. A subject is deemed to have incurred no time costs if the difference in the amount of time that she spends in decision problems of type O_iA_j is not significantly different from the amount of time she spends in decision problems of type O_iA_{j-10} for $j = 15$ (or $O_{i-10}A_j$, for $i = 15$). In other words, a subject is counted in the second row of Tables 12 and 13 if she made "no additional mistakes" as per the interpretation presented in the previous paragraph *and* she did not spend significantly more time on a type of decision problem as a result of irrelevant information.[24]

We present the summary statistics of WTP in Table 12 and the frequency of positive WTP amount in Table 13. The mean WTP and fraction of WTP greater than zero is positive and significant at the 5% level in each case. Additionally, a comparison between Tables 12 - 13 and Tables 9 - 10

[24]In all relevant analysis, "No Additional Mistakes" and "No Additional Mistakes or Time Costs" are defined at the subject-O_iA_j decision problem type level, independent of behavior in other decision problem types. As such, a subject could be considered to have made "No Additional Mistakes" in some decision problems, but not others, and may appear in some cells of Tables 12 and 13, but not all. These measures do not require any joint conditions over multiple decision problem types for a given subject.

reveals that the mean WTP and frequency of positive WTP closely matches that of the overall sample. In Tables 12 and 13, we can reject a null hypothesis $H_0 : \mu_{\text{No Additional Mistakes (or Time Costs)}} = \mu_{\text{Additional Mistakes (or Time Costs)}}$ in a Mann-Whitney test in each of the 16 instances. For example, in Table 12 the mean $WTP(A \mid O_5)$ of 4.226 ECU for the 62 subjects who make No Additional Mistakes is not significantly different than the mean $WTP(A \mid O_5)$ for the remaining 50 subjects in the Low Noise treatment at any standard α level. Note that in no instance in Tables 12 and 13 is there a significant difference; mean WTP and frequency of positive WTP, overall, does not depend on whether or not the subject made No Additional Mistakes (or Time Costs).

Additionally, let $y(I|J_k) = 1\{WTP(I|J_k) > 0\}$ indicate whether WTP to eliminate irrelevant information in the Ith dimension, given that there are k units of information in the Jth dimension, is positive. A Kolmogorov-Smirnov test of equality of distributions fails to reject the null $H_0 : F(y_{\text{additional mistakes}}(I|J_k)) = F(y_{\text{no additional mistakes}}(I|J_k))$ for each (I, J_k). Such tests also fail to reject the analogous null for WTP levels themselves ($H_0 : F(WTP_{\text{additional mistakes}}(I|J_k)) = F(WTP_{\text{no additional mistakes}}(I|J_k))$).

All of this taken together provides evidence that even subjects for whom irrelevant information neither affects the optimality of choice nor increases time spent on a decision problem prefer not to see such irrelevant information; there exists a preference for simplicity of the informational environment, even when irrelevant information has no effect on choice. Moreover, a brief look at responses to the open-ended question in our questionnaire reveals similar reasoning for some of our subjects. A subject who made no mistakes responded that "I chose [positive WTP amounts] to relax my eyes a little bit." Another responded that "either one [of eliminating irrelevant attributes or unavailable options] wouldn't be too helpful, but they still kind of help, so I put a low number and if I got it I got it, if I didn't, oh well." One possible explanation for this preference for simplicity may be that there is an additional dimension of cognitive effort spent on these decision problems that is not fully captured by mistake rates or time costs. Said another subject, "[...] unavailable options and attributes are distracting and cause me to *work harder* and longer when trying to calculate from options and attributes that are actually available. Therefore, I would be willing to pay ECU to get rid of them on the screen in order to work more efficiently and effectively" (emphasis added). To our knowledge, ours is the first study to identify such a preference, and this is the "cost of ignoring" in its purest form: there is a preference-based psychological consequence to having to ignore irrelevant information that is not captured by standard measures of the effect of irrelevant information on choice.

Table 12: WTP: No Additional Mistakes

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
No Additional Mistakes	4.226	4.000	3.930	4.133
	(.360)	(.324)	(.389)	(.387)
	62	68	43	45
No Additional Mistakes or Time Costs	4.130	4.031	4.192	4.146
	(.388)	(.338)	(.517)	(.396)
	54	65	26	41

Std. Errors in Parentheses
Sample mean > 0 at the $\alpha = 0.05$ level in each instance
Mann-Whitney $p > 0.1$ for $H_0 : \mu_{\text{No Additional Mistakes (or Time Costs)}} = \mu_{\text{Mistakes (or Time Costs)}}$ in each instance
Timeouts treated as Mistakes

Table 13: Frequency of Positive WTP: No Additional Mistakes

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
No Additional Mistakes	.919	.868	.837	.844
	(.035)	(.041)	(.057)	(.055)
	62	68	43	45
No Additional Mistakes or Time Costs	.907	.862	.885	.854
	(.040)	(.043)	(.064)	(.056)
	54	65	26	41

Std. Errors in Parentheses
Sample mean > 0 at the $\alpha = 0.05$ level in each instance
Mann-Whitney $p > 0.1$ for $H_0 : \mu_{\text{No Additional Mistakes (or Time Costs)}} = \mu_{\text{Mistakes (or Time Costs)}}$ in each instance
Timeouts treated as Mistakes

We summarize these results in Result 4:

Result 4 *There is a cost of ignoring irrelevant information that is not measured by mistake rates or time costs: subjects are willing to pay some amount not to see irrelevant information, even when irrelevant information does not affect choice.*

- *When measured in an analysis of WTP for subjects who make no additional mistakes in response to irrelevant information, this cost is positive.*

- *When measured in an analysis of WTP for subjects who make no additional mistakes in* *response to irrelevant information* and *spend no additional time in response to irrelevant information, this cost is again positive.*

4 Robustness Checks

In order to investigate to what extent our results are sensitive to the design specification used for these tasks, we conducted six additional sessions under alternative designs. Four of these sessions were conducted with alternative designs regarding Part 1 decision tasks and two of these sessions were conducted with alternative designs regarding the Part 2 willingness-to-pay tasks. These sessions are summarized in Table 14:

Table 14: Robustness Treatment Summary

Treatment	# of Sessions	# of Subjects	Part 1: Decisions	Part 2: BDM
8x8: Low Noise	2	32	40 Decisions	$O_8A_5 \rightarrow O_5A_5$ and $O_5A_8 \rightarrow O_5A_5$
8x8: High Noise	2	30	40 Decisions	$O_8A_8 \rightarrow O_5A_8$ and $O_8A_8 \rightarrow O_8A_5$
Alt-High Noise	2	30	40 Decisions	$O_{15}A_{15} \rightarrow O_5A_5$

In the treatments designated as "8x8" in the above table, decision tasks included a maximum of three unavailable options and three irrelevant attributes relative to the baseline in order to explore the effects of changing the parameter space on our main results. This resulted in decision task treatments O_5A_5, O_5A_8, O_8A_5, and O_8A_8. In the treatment named "Alt-High Noise", the decision tasks presented in Part 1 were the same as for the main treatments (i.e. O_5A_5, O_5A_{15}, $O_{15}A_5$, and $O_{15}A_{15}$) . However, in Part 2, subjects were asked a single WTP question eliciting WTP to move from $O_{15}A_{15}$ to O_5A_5.

All relevant results are presented in Appendix D. In this section, we will highlight several important results that further illuminate the main contributions of this paper.

4.1 Further Investigation of the Mistake Rate Function

In Subsection 3.1, we argue that our results indicate that mistake rates are not affected by unavailable options and irrelevant attributes *linearly*; the presence of both unavailable options and irrelevant attributes simultaneously amplifies the effect of irrelevant information on mistake rates in our main experimental task. However, an apt reader may notice that with five available options each with five relevant attributes in each treatment, our main design leads to the following counts of irrelevant cells of information displayed to subjects as described by Table 15.

Treatment	Irrelevant Cells
O_5A_5	0
O_5A_{15}	50
$O_{15}A_5$	50
$O_{15}A_{15}$	200

Table 15: Treatments and Irrelevant Information

So since we find higher mistake rates in treatment $O_{15}A_{15}$ only, this could be the result of either a) interaction between the two types of irrelevant information subjects handled or b) the presence of an additional 150 irrelevant cells relative to treatments O_5A_{15} and $O_{15}A_5$. Using the alternative 8x8 design, we can more precisely investigate the effect of the "size" of the irrelevant information set on mistake rates. The 8x8 design leads to the counts of irrelevant cells of information as described by Table 16. Note that the O_8A_8 case in this experiment has fewer irrelevant cells than either $O_{15}A_5$ or O_5A_{15} of the main experiments. If mistake rates in treatment O_8A_8 are higher than in treatment O_5A_5 in this new dataset and treatments $O_{15}A_5$ and O_5A_{15} in the main dataset, we can thus conclude that this is the result of some non-linearities in the mistake rate function and not simply the size of the set of irrelevant information.[25]

Table 28 in Appendix D.1 reports mistake rates across all decision problem types in the 8x8 treatments. The main messages of Tables 28 and 2 (for the main dataset) are similar: the interaction between unavailable options and irrelevant attributes are generates more suboptimal choice. Hence, we replicate our main finding on mistake rates with this additional dataset. Moreover, treatment

[25]We would, however, like to caution the reader against interpreting these results as evidence that unavailable options and irrelevant attributes can *never* affect welfare for a DM when presented alone. While this is mostly true in our experimental dataset, no single experiment (or set of experiments) can fully explore the parameter space of such decision problem such that we can precisely estimate the full specification of the mistake rate function. Our results simply indicate that there is sufficient evidence that, within the confines of our experimental design, the interaction between unavailable options and irrelevant attributes indeed matters.

Treatment	Irrelevant Cells
O_5A_5	0
O_5A_8	15
O_8A_5	15
O_8A_8	39

Table 16: Robustness Treatments and Irrelevant Information

O_8A_8 with 39 irrelevant cells displayed to subjects, has a mistake rate of 24.2%, which is higher than the mistake rates of both O_5A_{15} and $O_{15}A_5$ in the main dataset.[26] The results in Table 28 are robust to the exclusion of timeouts, reported in Table 29. Taken together, these additional analyses reveal that the central result contained in this work is indeed due to the presence of *both* unavailable options and irrelevant attributes, not simply due to the sheer amount of irrelevant information displayed.

Additionally, Appendix D.1 reports average Time spent in decision problems in the 8x8 treatments in Tables 30 through 32. Similar to our main dataset, Time spent in the 8x8 treatments increases in the presence of any irrelevant information, but more so for the addition of irrelevant attributes. Table 33 reports the incidence of Timeouts for the 8x8 treatments. Overall, timeouts occur in less than 3% of all observations in the 8x8 treatments, with the lowest incidence in decision problem type O_5A_5, similar to the main dataset.

4.2 Additional Willingness-to-Pay

The WTP results collected for the 8x8 treatments are similar to our results for WTP in the main experiments, where we observe positive WTP to eliminate irrelevant information (see Tables 34 and 35 in Appendix D.2). One thing worth noting here is that the average WTP is much lower in control experiments (Table 34 vs 9) and that subjects less frequently submit positive WTP amounts in control experiments than main experiments (Table 35 vs Table 10). This indicates that subjects perceived O_8A_8 as easier than $O_{15}A_{15}$ and hence they valued the elimination of unavailable options and irrelevant attributes much higher when they eliminate 10 rows or columns in a decision problem

[26] We also view mistake rates in the treatments used for robustness as lower bounds on true mistake rates. The mistake rate for the baseline treatment of this dataset was 16.8%, lower than the baseline mistake rate of 21.3% for the main dataset. This difference could be due to relative overall easiness of the robustness experiments with a maximum of O_8A_8 difficulty rather than $O_{15}A_{15}$ of the main experiments. Nevertheless it is important to note that even the lower bound of the mistake rate in O_8A_8 is higher than those observed in O_5A_{15} and $O_{15}A_5$.

than when they eliminate 3 of the same.

As previously mentioned, we've shown that *both* unavailable options and irrelevant attributes are necessary to generate an increase in the mistake rate, with mistake rates in treatment $O_{15}A_{15}$ being significantly higher than in the baseline. We've also shown that WTP to eliminate irrelevant information is sensitive to individual mistake rates, even though subjects are not provided with feedback regarding their performance in Part 1 of the experiment prior to submitting their WTP.

To bridge these two results, we conducted an additional two sessions where Part 2 of the experiment was altered to only ask a single WTP question, with subjects submitting their WTP to move from $O_{15}A_{15}$ to O_5A_5. Our central hypothesis is that, because mistake rates are higher *only* in $O_{15}A_{15}$, WTP for $O_{15}A_{15}$ to O_5A_5 should be significantly higher than any other WTP measure. If we had asked, say, three WTP measures ($O_{15}A_{15} \rightarrow O_5A_{15}$, $O_{15}A_{15} \rightarrow O_{15}A_5$, and $O_{15}A_{15} \rightarrow O_5A_5$) in these sessions, the subject may be primed to internally rank these three WTPs with $O_{15}A_{15} \rightarrow O_5A_5$ as the "most valuable" simply due to the relatively large number of irrelevant cells eliminated. To avoid this priming, we ask for WTP for $O_{15}A_{15} \rightarrow O_5A_5$ alone.

We find results consistent with our hypothesis, as indicated in Tables 36 and 37 in Appendix D.3. Mean WTP for $O_{15}A_{15} \rightarrow O_5A_5$ is 5.452 ECU, higher than any other WTP measure previously elicited in the main dataset. Moreover, approximately 84% of subjects submitted a positive WTP for $O_{15}A_{15} \rightarrow O_5A_5$, very similar to the frequency of positive WTP reported in Table 10. Hence, subjects report positive WTP for $O_{15}A_{15} \rightarrow O_5A_5$ with the same frequency as for the observations in our main experiment, but they are willing to pay higher amounts. These results provide more credence to the notion that WTP to eliminate irrelevant information closely tracks performance in Part 1, even absent any feedback.

5 Discussion

In this project, we set out to understand whether irrelevant information could ever be relevant in a given decision problem. Our results show that it is: unavailable options and irrelevant attributes can affect the optimality of choice. In this section we discuss some of the reasons behind our experimental design, the implications of our results, and the external relevance of this study.

We mentioned previously that screen size limitations prevent us from exploring the effects of the addition of more than ten unavailable options or irrelevant attributes. Adding any more information in either dimension would necessitate the use of filters, scrolling, text size changes across decision problems, etc., all of which would present confounds to our experimental design. We therefore cannot rule out that it is possible that there is free disposal of irrelevant information in a single dimension *up to a certain threshold*, beyond which one might observe effects on choice. It is easy to imagine examples where this mechanism can be reasonably assumed; adding a single out-of-stock TV to the in-store display of 10 available TVs at Costco likely has no effect on choice, but adding 50 might. If we take this threshold mechanism as given, one can then interpret our results in the following fashion: even when the addition of irrelevant information in a single dimension is not sufficient to affect choice, adding *both* unavailable options and irrelevant attributes in amounts lower than this threshold can affect choice. Moreover, even if this threshold-based mechanism were true, the threshold of information in one dimension required to affect choice is likely context-dependent, such that estimating such a threshold in a laboratory environment is likely not very generalizable. Nevertheless, we view further investigation of the characteristics of the mistake rate function as worthwhile for future research.

Our design is not crafted to figure out the exact functional form of the cost of processing different types of irrelevant information. Nevertheless, our findings indicate that even when each type of irrelevant information is within manageable range of processing cost, the subjects may start making more mistakes when they are jointly processed. We argue that this might be either due to the excess number of additional cells the subject processes when both types of irrelevant information are added or due to mentioned complementarities. Our 8x8 design is helpful to understand the role of the first effect. Note that in O_8A_8, the number of cells of irrelevant information presented in two dimensions is still less than the number of irrelevant cells in O_5A_{15} or $O_{15}A_5$ (39 vs 50). Finding higher mistake rates in O_8A_8 than O_5A_{15} or $O_{15}A_5$ is interpreted as evidence that it is not just the absolute number of cells that needs to be ignored determining the mistake rates, but also the interaction between the two dimensions. Note also that due to the differential difficulty levels of the two treatments and potential heterogeneity of subjects, one would expect lower mistake rates in O_8A_8. However, even with such bias we observed a higher mistake rate in O_8A_8 than in O_5A_{15}.

We view our results as being particularly relevant for issues of information disclosure. For example, there is some debate in the United States as to whether to require food manufacturers to disclose whether their products use genetically modified organisms (GMOs). In the absence of meaningful evidence of the negative health consequences of GMOs, the decision of whether to require such disclosure comes down to a discussion of consumer preferences. The logic might be that some consumers strictly prefer to consume only non-GMO products and so deserve to have access to this (relevant) information. Of course, some consumers have no such preference and, for them, the issue of whether GMOs are included in their food is irrelevant. Prior to gaining the knowledge contained in this project, it could reasonably be assumed that these consumers could simply freely dispose of this irrelevant GMO information when evaluating goods and so requiring disclosure should not impose any new costs on these consumers. However, we show that in some contexts it is possible that such irrelevant information can make people worse at making decisions. Moreover, even when someone does not make additional mistakes in the presence of irrelevant information, our willingness to pay results and the observed preferences for simplicity indicate that their welfare may be negatively affected directly by the inclusion of this information. All this is to say that our results would suggest a new trade-off that would need to be considered by policy makers in this GMO example; policy makers would now have to weigh the potential benefit of information disclosure to consumers who care about GMOs against the newly identified cost imposed by this irrelevant information on consumers who do not. Developing tools that allow consumers to filter the information they prefer to receive and allowing them sorting options based on their availability should be feasible at online shopping platforms.

6 Conclusion

In this paper we have presented the results of a novel experimental design to test for both i) effects of irrelevant information presented in a decision problem on choice and ii) willingness-to-pay to get rid of irrelevant information. Our main contribution is the identification of complementarities in irrelevant information presentation: both unavailable options and irrelevant attributes are necessary to generate increased mistake rates. This central result can shed light on the extant body of literature on decision theory and limited attention. Namely, we find that no leading models of choice, either rational and constrained or boundedly rational, can explain our data unless they are significantly modified. It is our hope that these results may provide direction for upcoming theoretical research intended to model choice in the presence of irrelevant information.

We should caution that our results don't suggest that not displaying such information is *always* optimal for the firm; displaying such information may be profitable for a number of reasons, including dynamic alternative sets and purchasing decisions, reference dependence (away from which we have abstracted in this work), such as the possibility that unavailable goods serve as decoy options that make certain available goods seem more attractive. However, our results do suggest that any agent considering whether to display such irrelevant information should recognize that there is a trade-off: a firm must weigh the potential immediate effect on profit relative to the effect on choice optimality on the part of the consumer that is induced by the presence of irrelevant information.

Further, we identify a "preference for simplicity". That is, for a subject who is faced with no material costs of having to ignore irrelevant information, we find that they are still willing to pay some amount to get rid of this information. This tells us that there are aspects of consumer preference in this environment that are not fully contained by measures intended to capture the notion of lost monetary value (i.e. mistake rates and time required to make a decision). It needs to be further investigated in future research how the complexity of presentation affects the algorithm used in decision making and how robust the preference for simplicity we document here is with respect to features of the decision problems used, such as color coded irrelevant information.

References

Becker, Gordon M, Morris H DeGroot, and Jacob Marschak, "Measuring Utility by a Single-response Sequential Method," *Behavioral Science*, 1964, *9* (3), 226–232.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Salience Theory of Choice under Risk," *Quarterly Journal of Economics*, 2012, *127* (3), 1243–1285.

_ , _ , and _ , "Salience and Consumer Choice," *Journal of Political Economy*, 2013, *121* (5), 803–843.

_ , _ , and _ , "Competition for Attention," *The Review of Economic Studies*, 2016, *83* (2), 481–513.

Caplin, Andrew, Mark Dean, and Daniel Martin, "Search and Satisficing," *American Economic Review*, 2011, *101* (7), 2899–2922.

Cohen, Patricia, Jacob Cohen, Leona S Aiken, and Stephen G West, "The problem of units and the circumstance for POMP," *Multivariate Behavioral Research*, 1999, *34* (3), 315–346.

Farquhar, Peter H and Anthony R Pratkanis, "Decision Structuring with Phantom Alternatives," *Management Science*, 1993, *39* (10), 1214–1226.

Filiz-Ozbay, Emel, John C Ham, John H Kagel, and Erkut Y Ozbay, "The Role of Cognitive Ability and Personality Traits for Men and Women in Gift Exchange Outcomes," *Experimental Economics*, 2016, *https://doi.org/10.1007/s10683-016-9503-2.*

Fischbacher, Urs, "z-Tree: Zurich Toolbox for Ready-made Economic Experiments," *Experimental Economics*, 2007, *10* (2), 171–178.

Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen Weinberg, "Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model," *American Economic Review*, 2006, *96* (4), 1043–1068.

Kahneman, Daniel and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 1979, *47* (2), 263–292.

Klabjan, Diego, Wojciech Olszewski, and Asher Wolinsky, "Attributes," *Games and Economic Behavior*, 2014, *88*, 190–206.

Kőszegi, Botond and Adam Szeidl, "A model of focusing in economic choice," *The Quarterly journal of economics*, 2012, *128* (1), 53–104.

Lleras, Juan Sebastian, Yusufcan Masatlioglu, Daisuke Nakajima, and Erkut Y Ozbay, "When More is Less: Limited Consideration," *Journal of Economic Theory*, 2017, *170*, 70–85.

Manzini, Paola and Marco Mariotti, "Sequentially Rationalizable Choice," *American Economic Review*, 2007, *97* (5), 1824–1839.

_ **and** _ , "Categorize Then Choose: Boundedly Rational Choice and Welfare," *Journal of the European Economic Association*, 2012, *10* (5), 1141–1165.

_ **and** _ , "Stochastic Choice and Consideration Sets," *Econometrica*, 2014, *82* (3), 1153–1176.

Masatlioglu, Yusufcan, Daisuke Nakajima, and Erkut Y Ozbay, "Revealed Attention," *American Economic Review*, 2012, *102* (5), 2183–2205.

Oprea, Ryan, "What is Complex?," *working paper*, 2019.

Reutskaja, Elena, Rosemarie Nagel, Colin F Camerer, and Antonio Rangel, "Search Dynamics in Consumer Choice under Time Pressure: An Eye-tracking Study," *American Economic Review*, 2011, *101* (2), 900–926.

Richter, Sen Geng Leonardo Pejsachowicz Michael, "Breadth versus Depth," 2017.

Sanjurjo, Adam, "Search with multiple attributes: Theory and empirics," *Games and Economic Behavior*, 2017, *104*, 535–562.

Soltani, Alireza, Benedetto De Martino, and Colin Camerer, "A Range-normalization Model of Context-dependent Choice: A New Model and Evidence," *PLoS Computational Biology*, 2012, *8* (7), e1002607.

Appendix A Instructions

Part 1

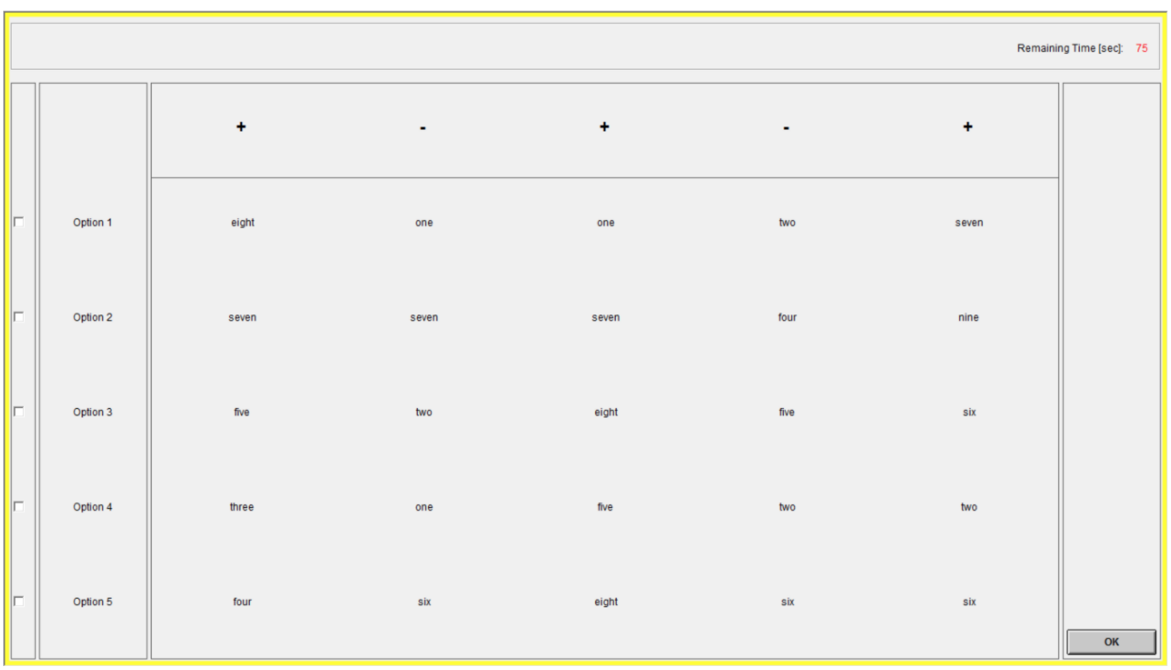
Thank you for participating in this experiment. In this session you will work alone and are not permitted to talk with any other participant. At this time, please be sure that your cell phone is turned off. At no point during the experiment are you permitted to use your cell phone or any other personal electronic device.

The Experiment

The experiment today is broken into two parts. These are the instructions for Part 1 of the experiment. At the conclusion of Part 1, the experimenter will hand out and read instructions for Part 2 before proceeding. Your earnings in Part 1 and Part 2 are independent.

This is an experiment on decision-making. In each of 40 periods, you will be asked to choose one from among a number of options. You will have at most 1 minute and 15 seconds (or 75 seconds) to make this decision in each period. Each option is described by a number of attributes. Attributes take on the numbers 1-9 with each number being equally likely to be shown. The value of each option is the result of the addition and/or subtraction of these attributes and is measured in Experimental Currency Units (or ECU). The exchange rate will be as follows: 1 USD = 10 ECU. You will know whether to add or subtract each attribute based on column headers in the displayed data. While calculating these values, you will not be permitted to use a calculator or pen and paper.

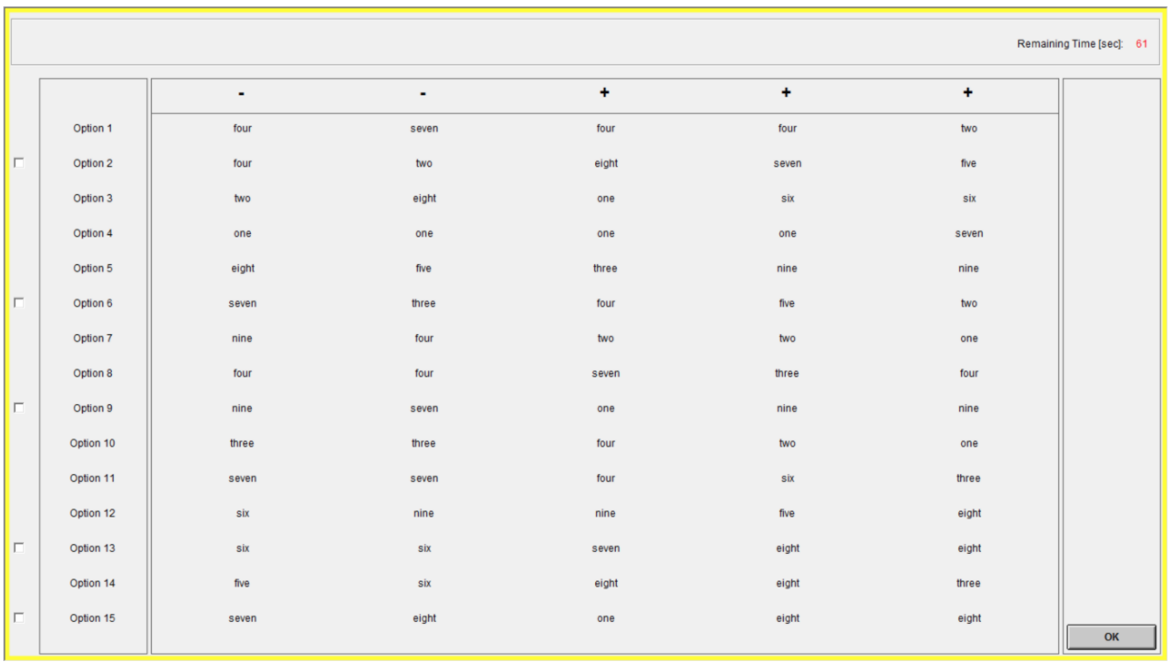
In each period, you will see a screen that looks similar to the one below:



Notice that Option 1 is accompanied by 5 numbers (shown in words) in a grid to its right. The value of Option 1 is simply the result of adding or subtracting the numbers in its corresponding row. You will know whether to add a number or subtract it based on the **plus** or **minus** sign in the column header row. Thus, the value of Option 1 is 13 ECU (or eight - one + one - two + seven = ECU). The values of Options 2-5 can be calculated in a similar way.

Variations

In each of the 40 periods, the number of available options is the same (5). However, the number of displayed options will vary. In other words, there may be some options displayed on your screen that you will not be able to select. Consider the following example:

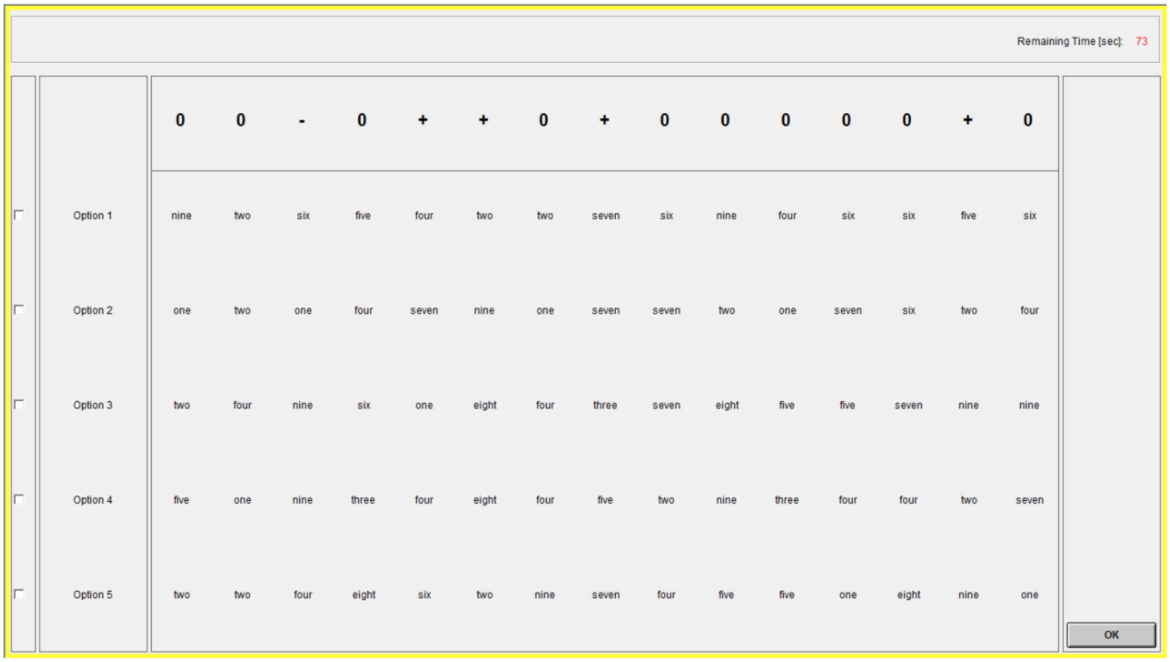

Remaining Time [sec]: 61

	-	-	+	+	+
Option 1	four	seven	four	four	two
Option 2	four	two	eight	seven	five
Option 3	two	eight	one	six	six
Option 4	one	one	one	one	seven
Option 5	eight	five	three	nine	nine
Option 6	seven	three	four	five	two
Option 7	nine	four	two	two	one
Option 8	four	four	seven	three	four
Option 9	nine	seven	one	nine	nine
Option 10	three	three	four	two	one
Option 11	seven	seven	four	six	three
Option 12	six	nine	nine	five	eight
Option 13	six	six	seven	eight	eight
Option 14	five	six	eight	eight	three
Option 15	seven	eight	one	eight	eight

OK

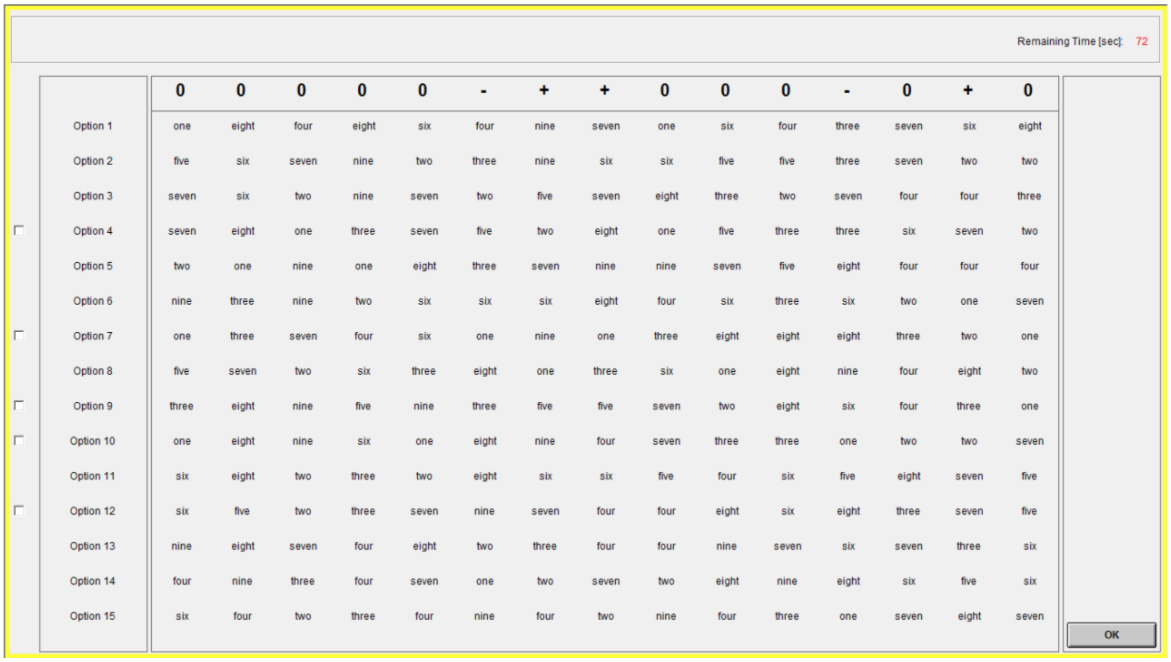
Note that each option still has 5 attributes in the grid. However, now Option 1 cannot be selected (this can be seen from the absence of a checkbox to the left of "Option 1). You may only select one from the following: Option 2, Option 6, Option 9, Option 13, or Option 15. Which options are available will vary between periods. Also note that the value of each option is calculated as in the first example. For example, the value of Option 2 is 14 ECU (or - four - two + eight + seven + five = 14 ECU).

In each of the 40 periods, the number of attributes per option will vary. However, in some periods, some of these attributes may be multiplied by **zeros** instead of being added or subtracted when calculating the value of each option. Consider the following example:



Note that all displayed options are available (you can see this from the checkbox to the left of each option label). However, there are additional attributes for each option (now there are 15). In contrast to the previous examples, some of these attributes are now multiplied by 0 instead of being added or subtracted when determining the value of each option. This can be seen from the zeros in the column header. For example, the value of Option 1 is 12 ECU (-six + four + two + seven + five = 12 ECU). Notice that in this calculation, the first and second attributes (nine and two) were not included because they have a 0 in the column header. The same is true for any value for which there is a zero in the column header. Which attributes have zeros (and pluses or minuses) will vary by period.

Finally, in some periods there will be additional attributes and unavailable options. Consider the following example:



Remaining Time [sec]: 72

		0	0	0	0	0	-	+	+	0	0	0	-	0	+	0
	Option 1	one	eight	four	eight	six	four	nine	seven	one	six	four	three	seven	six	eight
	Option 2	five	six	seven	nine	two	three	nine	six	six	five	five	three	seven	two	two
	Option 3	seven	six	two	nine	seven	two	five	seven	eight	three	two	seven	four	four	three
☐	Option 4	seven	eight	one	three	seven	five	two	eight	one	five	three	three	six	seven	two
	Option 5	two	one	nine	one	eight	three	seven	nine	nine	seven	five	eight	four	four	four
	Option 6	nine	three	nine	two	six	six	six	eight	four	six	three	six	two	one	seven
☐	Option 7	one	three	seven	four	six	one	nine	one	three	eight	eight	eight	three	two	one
	Option 8	five	seven	two	six	three	eight	one	three	six	one	eight	nine	four	eight	two
☐	Option 9	three	eight	nine	five	nine	three	five	five	seven	two	eight	six	four	three	one
☐	Option 10	one	eight	nine	six	one	eight	nine	four	seven	three	three	one	two	two	seven
	Option 11	six	eight	two	three	two	eight	six	six	five	four	six	five	eight	seven	five
☐	Option 12	six	five	two	three	seven	nine	seven	four	four	eight	six	eight	three	seven	five
	Option 13	nine	eight	seven	four	eight	two	three	four	four	nine	seven	six	seven	three	six
	Option 14	four	nine	three	four	seven	one	two	seven	two	eight	nine	eight	six	five	six
	Option 15	six	four	two	three	four	nine	four	two	nine	four	three	one	seven	eight	seven

OK

Note that Option 1 is **unavailable** (you can see this from the absence of any checkbox to its left). Also note that there are several columns with **zeros** in the column header. The value of Option 4 is 9 ECU (-five + two + eight -three + seven= 9 ECU). Notice that the 1st through 5th attributes were not included for Option 4 (seven, eight, one, three, and seven) since these have zeros in the column header. The same is true for any column of attributes for which there is a zero in the column header. Again, which columns have zeros (and pluses/minuses) and which options are unavailable will vary by period.

Time Limit

In each period, you have 1 minute and 15 seconds (75 seconds) to submit your choice of option. You must submit your option by checking the checkbox to its left and clicking the OK button at the bottom right of the screen. If you **do not** submit your selection by clicking the OK button prior to the end of the period (i.e. within 75 seconds of the period starting), your selection will not be submitted and **you will be paid nothing** for that period. Only by selecting an option and clicking OK prior to the end of the period will your choice be submitted for the period.

Earnings

In each period, your per-period payoff is simply the value of the option you have chosen. In each of these periods, the values for each option have been chosen so that despite being the sum of both positive and negative numbers, the **value of each available option is positive**. That is, no matter which option you choose, money will never be taken away from you. 10 periods will be chosen at random and your cash earnings will be the sum of the per-period payoffs for these 10 periods, converted to US Dollars. The exchange rate will be as follows: \$1 USD = 10 ECU. Your total cash earnings will be added to your show-up fee of $7.00 and your earnings from Part 2 of this experiment.

You will be paid your earnings privately in cash before you leave the lab.

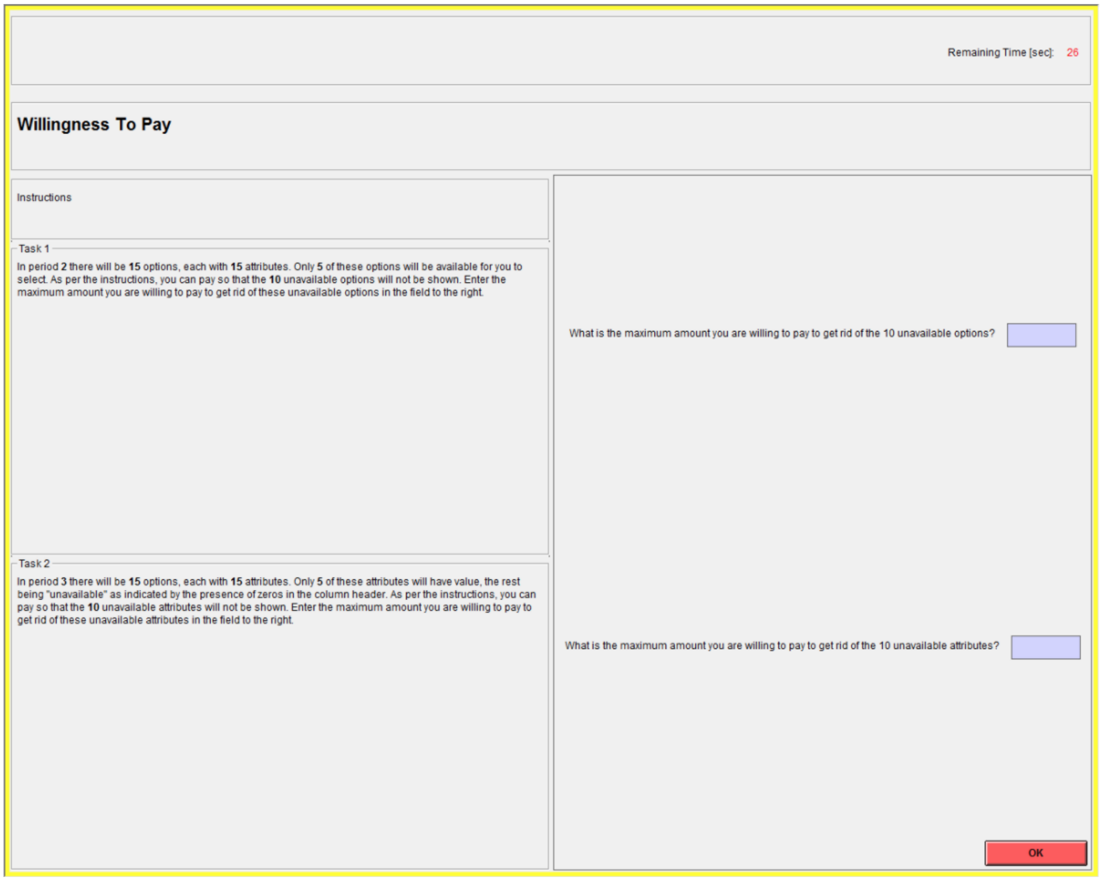
Part 2

Thank you for participating in Part 2 of the experiment.

You will be faced with 3 periods in which you make decisions: **1** period in which you will be asked to submit two numbers (explained in detail below), and **2** periods of decision environments where you will choose from among a number of options, each described by a number of attributes. Some of these options will be unavailable for you to select and some of the attributes will not have value (as indicated by the presence of a zero in the header row). However, you will have the opportunity to pay some amount (in ECU) to get rid of these unavailable options and attributes.

In period 1, you will be asked to complete **two tasks** which will affect what you see in periods 2 and 3: **Task 1** is to enter the maximum amount you are willing to pay (in ECU) to get rid of the unavailable options to be presented in period 2, and **Task 2** is to enter the maximum amount you are willing to pay to get rid of the attributes that have no value (as indicated by the zeros in the column header; these will be referred to as unavailable attributes for the remainder of the instructions) to be presented in period 3. Note that decisions in each task will correspond to outcomes in two separate subsequent periods: Task 1 affects what you see in period 2 and Task 2 affects what you see in period 3.

The screenshot below displays what this environment will look like in period 1:



For **Task 1** and **Task 2**, two random numbers will be drawn from 0 ECU to 15 ECU. These two numbers may not be the same. These will be the selling prices for getting rid of the unavailable options or unavailable attributes, respectively. If the maximum amount you are willing to pay to get rid of unavailable options that you entered for Task 1 is above the selling price for Task 1, you pay the selling price and you will not see these unavailable options in period 2. If the maximum amount you are willing to pay to get rid of unavailable attributes is higher than the selling price for Task 2, you pay the selling price and you will not see these unavailable attributes in period 3. However, if either (or both) of the selling prices are above the maximum amount you are willing to pay, entered in period 1 for Task 1 and Task 2, you pay nothing and the unavailable options or unavailable attributes will be shown in the respective period.

Note that you enter both of these numbers indicating your maximum willingness to pay to simplify the environments at the same time and **before** you know the result of either random number draw. That is, when you enter the maximum amount you are willing to pay to get rid of unavailable options, you will not know whether you have been able to get rid of unavailable attributes, and when you enter the maximum amount you are willing to pay to get rid of unavailable attributes, you will not know whether you have been able to get rid of the unavailable options. Also note that it is in your best interest not to overstate (or understate) the maximum amount you are willing to pay in either Task 1 or Task 2. Suppose you are willing to pay at most 5 ECU to get rid of either unavailable options or attributes. If the random is drawn and you enter exactly 5

ECU, there are two potential outcomes: either the number is higher than 5, in which case you pay nothing and the unavailable options or attributes will be displayed in the respective period, or the number is less than 5 , say 4 ECU. In this case, you pay the 4 ECU and the unavailable options or attributes are not shown. Note that you were willing to pay **at most** 5 ECU, but only had to pay 4 ECU.

Suppose instead that you overstate this amount in either Task 1 or Task 2 by entering, say, 6 ECU. Then it could be the case that the number drawn is 5.5, for example, which is less than 6 (which you have entered) but greater than 5, the true maximum amount that you are willing to pay. Because you have entered 6, you will pay the drawn amount, 5.5 ECU, which is more than you originally were willing to pay - you will have gotten rid of unavailable options or attributes, but paid more than the maximum amount you were willing to pay. On the other hand, suppose you understate this amount by entering 4 ECU. Then if the random number drawn is, say, 4.5 ECU, you will not be able to get rid of the unavailable options or attributes, but would be willing to pay this amount. Only by entering the actual maximum amount you are willing to pay in Task 1 and Task 2 will you both a) prevent having to pay more than this amount (by overstating) and b) prevent missing out on paying a lesser amount when it is profitable to do so (by understating).

Decision Environments

These decision environments will appear exactly as you have seen them in Part 1. Again, you will have 75 seconds to submit your decision. If you do not submit your chosen option by that time, no option will be submitted and you will be paid nothing for that period.

By default, in period 2 there will be 15 options, each with 15 attributes. Only 5 of these options will be available for you to select and only 5 of these attributes will have value (as indicated by the presence of a + or - in the column header). You can pay to have the **10 unavailable options** not displayed in this period. No matter what, each of the displayed options will have 15 attributes, 10 of which will have zeros in the column header. Whether the 10 unavailable options are displayed depends on the result of your choice in Task 1, described in detail above.

By default, in period 3 there will be 15 options, each with 15 attributes. Only 5 of these attributes will have value - the rest are unavailable (as indicated by the presence of zeros in the column header) and only 5 of these options will be available for you to select. You can pay to have the **10 unavailable attributes** not displayed in this period. No matter what, there will be 15 options displayed (5 of which will be available for selection). Whether the 10 unavailable attributes are displayed depends on the result of your choice in Task 2, described in detail above.

Payoff Calculation

In each of periods 2 and 3, your per-period payoff is simply the value of the option you have chosen. In each of these periods, the values for each option have been chosen so that despite being the sum of both positive and negative numbers, the **value of each available option is positive**. That is, no matter which option you choose, money will never be taken away from you.

Choices in all periods contribute to your payoffs for this part of the experiment. In the first period, if you are able to get rid of either unavailable options or attributes or both, the relevant random number that was drawn is subtracted from your payoffs. In each of the decision periods, the value of the option you have chosen will be added to your payoffs, with the value of each option calculated as in Part 1 of this experiment. The exchange rate will be as follows: \$1 USD = 10 ECU. Your total cash earnings will be added to your show-up fee of \$7.00 and your earnings from Part 1 of this experiment.

You will be paid your earnings privately in cash before you leave the lab.

Appendix B Additional Analyses

B.1 Additional Aggregate Results

Table 17: Mistake Rates: Excluding Timeouts

		O_5	O_{15}
A_5	Mean	0.193	0.201
	Std Error	0.013	0.013
	N	222	222
A_{15}	Mean	0.193	0.299
	Std Error	0.012	0.016
	N	222	222

$p = 0.000$ for $O_{15}A_5 \rightarrow O_{15}A_{15}$, $O_5A_{15} \rightarrow O_{15}A_{15}$, and $O_5A_5 \rightarrow O_{15}A_{15}$
$p > 0.100$ otherwise.

Table 18: Time: Timeouts Treated as Maximum Time

		O_5	O_{15}
A_5	Mean	49.200	50.405
	Std Error	0.713	0.677
	N	222	222
A_{15}	Mean	53.769	57.374
	Std Error	0.779	0.782
	N	222	222

p = 0.00 for $O_5A_5 \rightarrow O_5A_{15}$, $O_{15}A_5 \rightarrow O_{15}A_{15}$,
$O_5A_{15} \rightarrow O_{15}A_{15}$, $O_5A_5 \rightarrow O_{15}A_{15}$, and $O_{15}A_5 \rightarrow O_5A_{15}$
$p > 0.10$ for $O_5A_5 \rightarrow O_{15}A_5$

Table 19: Time: Correct

		O_5	O_{15}
A_5	Mean	48.240	49.641
	Std Error	0.727	0.662
	N	222	220
A_{15}	Mean	52.615	56.613
	Std Error	0.769	0.776
	N	222	222

p = 0.00 for $O_5A_5 \rightarrow O_5A_{15}$, $O_{15}A_5 \rightarrow O_{15}A_{15}$,
$O_5A_{15} \rightarrow O_{15}A_{15}$, $O_5A_5 \rightarrow O_{15}A_{15}$, and $O_{15}A_5 \rightarrow O_5A_{15}$
$p > 0.10$ for $O_5A_5 \rightarrow O_{15}A_5$
Conditional on Correct

B.2 Time Cost Results

Table 20: Time Regressions with Alternative Time Thresholds

	(1)	(2)	(3)
	$t < 73$	$t < 70$	$t < 65$
Options	-0.862	0.373	1.605*
	(0.929)	(0.950)	(0.975)
Attributes	4.027***	3.405***	2.821***
	(0.913)	(0.958)	(1.047)
Options * Attributes	1.422***	0.981*	-0.437
	(0.513)	(0.562)	(0.586)
Period	-0.224***	-0.223***	-0.123
	(0.071)	(0.073)	(0.076)
Period^2	-0.001	-0.000	-0.002
	(0.002)	(0.002)	(0.002)
Cognitive Score	10.633***	11.483***	12.505***
	(4.068)	(3.845)	(3.741)
Female	-2.470*	-2.159*	-2.190*
	(1.319)	(1.248)	(1.177)
Economics/Business	-2.272	-2.347	-1.977
	(1.553)	(1.451)	(1.351)
English	-3.075**	-2.450*	-2.288*
	(1.520)	(1.392)	(1.305)
Position	0.131***	0.094**	0.040
	(0.043)	(0.044)	(0.046)
Positive	-1.270***	-0.964***	-0.876***
	(0.267)	(0.262)	(0.268)
Attribute Complexity	0.134	0.181	0.127
	(0.224)	(0.239)	(0.267)
Option Complexity	0.614***	0.276	0.007
	(0.218)	(0.230)	(0.239)
Observations	8169	7438	6312
Session FE	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Each Model: 222

Marginal effects from tobit regressions censored below by 0 and above by 75.

Robust standard errors are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Time Regressions with Alternative Time Thresholds

	(1)	(2)	(3)
	$t < 73$	$t < 70$	$t < 65$
Options	-0.944	0.288	1.302
	(0.984)	(0.980)	(1.004)
Attributes	5.016***	4.748***	3.858***
	(1.082)	(1.147)	(1.250)
Options * Attributes	3.242***	2.981***	1.772***
	(0.532)	(0.545)	(0.530)
Period	-0.157**	-0.162**	-0.074
	(0.066)	(0.067)	(0.067)
Period^2	-0.001	-0.001	-0.003*
	(0.002)	(0.002)	(0.002)
Cognitive Score	6.843**	7.439**	8.741***
	(3.210)	(3.000)	(2.810)
Female	-1.422	-1.153	-1.288
	(1.103)	(1.017)	(0.913)
Economics/Business	-2.704**	-2.948**	-2.571**
	(1.346)	(1.235)	(1.121)
English	-2.033	-1.414	-1.317
	(1.345)	(1.172)	(1.057)
Position	0.186***	0.138***	0.115***
	(0.044)	(0.044)	(0.045)
Positive	-0.946***	-0.800***	-0.745**
	(0.280)	(0.282)	(0.294)
Attribute Complexity	-0.096	-0.198	-0.134
	(0.291)	(0.311)	(0.333)
Option Complexity	0.537**	0.190	-0.087
	(0.236)	(0.246)	(0.259)
Observations	6432	5913	5036
Session FE	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Each Model: 222

Marginal effects from tobit regressions censored below by 0 and above by 75.

Robust standard errors are clustered at the Subject level

All models conditional on Correct

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 GPA Robustness Checks

Table 22: Mistake Rate Regressions with GPA

	(1) Mistake	(2) Mistake	(3) Mistake	(4) Mistake	(5) Mistake†
Options	0.010	0.014	-0.022	-0.045	-0.062**
	(0.011)	(0.012)	(0.013)	(0.029)	(0.029)
Attributes	-0.000	0.003	-0.004	-0.014	0.013
	(0.012)	(0.012)	(0.013)	(0.029)	(0.029)
Options * Attributes	0.086***	0.077***	0.085***	0.086***	0.091***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
Period	-0.007***	-0.007***	-0.008***	-0.007***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Period^2	0.0002***	0.0002***	0.0002***	0.0002***	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPA		-0.214***	-0.214***	-0.214***	-0.223***
		(0.065)	(0.065)	(0.065)	(0.065)
Female		0.078***	0.078***	0.078***	0.078***
		(0.022)	(0.022)	(0.022)	(0.022)
Economics/Business		-0.010	-0.010	-0.010	0.003
		(0.026)	(0.026)	(0.026)	(0.027)
English		-0.006	-0.006	-0.006	-0.018
		(0.023)	(0.023)	(0.023)	(0.024)
Position			0.005***	0.005***	0.006***
			(0.001)	(0.001)	(0.001)
Positive			-0.032***	-0.034***	-0.033***
			(0.008)	(0.008)	(0.009)
Attribute Complexity				0.003	0.000
				(0.008)	(0.007)
Option Complexity				0.006	0.010
				(0.007)	(0.007)
Observations	8555	8121	8121	8121	8440
Session FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Baseline: 222

11 Subjects with missing GPA excluded from models with GPA

†: Timeouts treated as mistakes

Marginal effects from logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Time Regressions with GPA

	(1)	(2)	(3)	(4)	(5)	(6)
	Time	Time	Time	Time	Time†	Time‡
Options	2.215***	2.158***	1.012**	-1.920*	-1.324	-1.670*
	(0.381)	(0.397)	(0.485)	(0.985)	(0.994)	(0.940)
Attributes	5.655***	5.735***	5.467***	4.993***	5.052***	4.715***
	(0.430)	(0.441)	(0.449)	(0.949)	(1.111)	(0.899)
Options * Attributes	1.734***	1.722***	1.969***	2.096***	3.407***	1.942***
	(0.499)	(0.517)	(0.517)	(0.521)	(0.551)	(0.502)
Period	-0.394***	-0.394***	-0.412***	-0.402***	-0.185***	-0.347***
	(0.078)	(0.081)	(0.081)	(0.081)	(0.069)	(0.076)
Period^2	0.002	0.002	0.003	0.003	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GPA		8.650*	8.648*	8.649*	5.985*	8.765**
		(4.455)	(4.455)	(4.455)	(3.418)	(4.359)
Female		-2.545*	-2.545*	-2.546*	-1.664	-2.560*
		(1.387)	(1.387)	(1.387)	(1.136)	(1.357)
Economics/Business		-1.135	-1.137	-1.137	-2.236*	-1.276
		(1.582)	(1.582)	(1.582)	(1.354)	(1.542)
English		-3.415**	-3.416**	-3.416**	-1.974	-3.226**
		(1.585)	(1.585)	(1.585)	(1.423)	(1.549)
Position			0.161***	0.199***	0.199***	0.186***
			(0.041)	(0.043)	(0.046)	(0.042)
Positive			-1.180***	-1.374***	-0.984***	-1.359***
			(0.275)	(0.280)	(0.273)	(0.269)
Attribute Complexity				0.126	-0.004	0.151
				(0.233)	(0.301)	(0.220)
Option Complexity				0.809***	0.595**	0.751***
				(0.231)	(0.240)	(0.219)
Observations	8880	8440	8440	8440	6332	8440
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Baseline: 222

11 Subjects with missing GPA excluded from models with GPA

†: Conditional on Correct

‡: Timeouts treated as Time = 75 seconds

Marginal effects reported from tobit regressions censored below by 0 and above by 75

Robust standard errors are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: WTP Regressions with GPA

	(1) WTP	(2) WTP	(3) WTP	(4) WTP > 0	(5) WTP > 0	(6) WTP > 0
Mistakes	0.413***	0.454***	0.317***	0.379***	0.405***	0.346**
	(0.102)	(0.108)	(0.119)	(0.124)	(0.127)	(0.157)
Time	0.003	0.003	0.003	0.002	0.001	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Attributes	0.191	0.181	0.317	0.022	0.023	0.209
	(0.156)	(0.164)	(0.279)	(0.159)	(0.175)	(0.299)
High Noise	2.296*	2.470**	1.043	0.793	0.681	1.856
	(1.200)	(1.203)	(2.416)	(1.401)	(1.531)	(3.307)
Female		-0.353	-0.298		0.470	0.456
		(0.450)	(0.441)		(0.514)	(0.503)
GPA		-0.387	-0.454		-0.708	-0.662
		(1.179)	(1.151)		(1.086)	(1.098)
High Noise * Mistakes			0.292			0.117
			(0.205)			(0.248)
High Noise * Time			0.001			-0.002
			(0.004)			(0.005)
High Noise * Attributes			-0.255			-0.436
			(0.334)			(0.339)
Constant	0.394	0.580	1.059	-0.038	0.485	0.240
	(1.281)	(1.436)	(1.735)	(1.363)	(1.698)	(1.839)
Observations	444	422	422	386	366	366
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Baseline: 222

11 Subjects with missing GPA dropped from Models 2-6

Additional 29 Subjects dropped from Models 4 - 6 because session FE perfectly predicts WTP > 0

Models 1 - 3: Tobit regression specifications with lower limit of 0 and upper limit of 15

Models 4-6: Logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Regressions Under Alternative Complexity Measures

In Section 3, we introduce a complexity measure to determine whether the mistake rate in each treatment depended on the number of "skips" in the evaluation process for either attributes or options. In this appendix, we present regression results where we investigate whether mistakes depend on attribute and option complexity under alternative versions of this measure.

First, we introduce "Opt Comp w/ 0" and "Att Comp w/ 0" measures that are the measures we used previously in the body of the text, but including leading and trailing zeros. Second, we introduce "Opt Comp 1st" and "Opt Comp 2nd," with the analogous measures defined for Attributes. These measures take our aggregate measures and split them into the "first half" and "second half" of the evaluation process in each dimension. In other words, "Opt Comp 1st" is "the number of skips in Options for the first 7 Options" and "Opt Comp 2nd" is "the number of skips in Options for the last 8 Options." "Att Comp 1st" and "Att Comp 2nd" are defined analogously.

The hypothesis here is that it is possible, given order effects documented by the effects of the Position variable in previous regressions, that complexity might matter more for the first several options/attributes than for later options/attributes. We find that this is the case for the mistake rate regressions as the coefficient of Opt Comp 1st is higher than that of Opt Comp 2nd and the coefficient of Att Comp 1st is higher than its counterpart in the relevant columns of Table 25. This is also the case for the time regressions in Table 26.

In each of the tables below, models are conducted for observations from our main experiment. Each is restricted to the relevant subsample where the complexity measure is meaningful, as indicated in the last row of the table.

Table 25: Mistake Rate Regressions

	(1) Mistake	(2) Mistake	(3) Mistake	(4) Mistake	(5) Mistake	(6) Mistake
Period	-0.006***	-0.007***	-0.004*	-0.004**	-0.007***	-0.005**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Period^2	0.0002***	0.0002***	0.0001**	0.0001***	0.0002***	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive Score	-0.217***	-0.274***	-0.226***	-0.234***	-0.274***	-0.225***
	(0.063)	(0.069)	(0.069)	(0.064)	(0.069)	(0.069)
Female	0.077***	0.086***	0.077***	0.078***	0.087***	0.077***
	(0.021)	(0.023)	(0.024)	(0.022)	(0.023)	(0.024)
Economics/Business	-0.008	-0.013	-0.013	-0.010	-0.013	-0.013
	(0.025)	(0.028)	(0.027)	(0.026)	(0.028)	(0.027)
English	-0.003	-0.001	-0.008	-0.001	-0.001	-0.008
	(0.022)	(0.027)	(0.024)	(0.023)	(0.027)	(0.024)
Opt Comp w/ 0		-0.001		0.019***		
		(0.008)		(0.003)		
Att Comp w/ 0			0.016*	0.019***		
			(0.008)	(0.003)		
Opt Comp 1st					0.025**	
					(0.010)	
Opt Comp 2nd					-0.003	
					(0.009)	
Att Comp 1st						0.039***
						(0.009)
Att Comp 2nd						-0.024**
						(0.011)
Observations	8555	4269	4219	6393	4269	4219
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Decision Problems	All	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$	$O_{15}A_5$, $O_{15}A_{15}$, O_5A_{15}	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$

Standard errors in parentheses

Number of Subjects in Each Model: 222

Marginal effects from logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Time Regressions

	(1) Time	(2) Time	(3) Time	(4) Time	(5) Time	(6) Time
Period	-0.261***	-0.180*	-0.232**	-0.176**	-0.190**	-0.246***
	(0.073)	(0.096)	(0.095)	(0.081)	(0.095)	(0.094)
Period^2	-0.0001	-0.001	-0.001	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cognitive Score	9.936**	9.587**	13.980***	11.181***	9.590**	13.993***
	(4.143)	(4.223)	(4.477)	(4.249)	(4.223)	(4.473)
Female	-2.537*	-2.542*	-3.193**	-2.691*	-2.540*	-3.183**
	(1.338)	(1.364)	(1.475)	(1.374)	(1.363)	(1.475)
Economics/Business	-2.302	-2.324	-2.051	-2.160	-2.324	-2.050
	(1.585)	(1.596)	(1.721)	(1.613)	(1.596)	(1.719)
English	-3.134**	-3.174**	-3.389**	-3.177**	-3.175**	-3.391**
	(1.536)	(1.512)	(1.609)	(1.527)	(1.512)	(1.608)
Opt Comp w/ 0		0.724***		0.761***		
		(0.213)		(0.072)		
Att Comp w/ 0			0.597***	1.416***		
			(0.220)	(0.101)		
Opt Comp 1st					0.898***	
					(0.298)	
Opt Comp 2nd					0.706***	
					(0.253)	
Att Comp 1st						0.672***
						(0.212)
Att Comp 2nd						0.157
						(0.344)
Observations	8555	4269	4219	6393	4269	4219
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Decision Problems	All	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$	$O_{15}A_5$, $O_{15}A_{15}$, O_5A_{15}	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$

Standard errors in parentheses

Number of Subjects in Each Model: 222

Marginal effects reported from tobit regressions censored below by 0 and above by 75

Robust standard errors are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C Learning Effects

In order to investigate the possibility of differential learning across decision problem types, we first run mistake rate model specification 5 from Table 4 separately for each type. These results are included below. Note that our results on Period and Period^2 are qualitatively similar across all decision problem types.

Table 27: Differential Learning: Mistakes

	(1) Mistake†	(2) Mistake†	(3) Mistake†	(4) Mistake†
Period	-0.014***	-0.007**	-0.009***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.004)
Period^2	0.0003***	0.0002**	0.0002***	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2220	2220	2220	2220
Session FE	Yes	Yes	Yes	Yes
Decision Problem Type	$\mathrm{O}_5 A_5$	$\mathrm{O}_5 A_{15}$	$\mathrm{O}_{15} A_5$	$\mathrm{O}_{15} A_{15}$

Standard errors in parentheses
Number of Subjects in Each Model: 222
†: Timeouts treated as mistakes
Marginal effects from logit regression specifications
Robust standard errors reported are clustered at the Subject level
Demographic controls, Position, Positive, and Complexity Measures included in each model
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27 provides initial evidence that learning is similar across all decision problem types. However, note that in our experiment, a subject encountered 40 decision problems, 10 of each of four types. The order was randomized at the session-subject level, so the effect of Period within a decision problem type would not be easily comparable across decision problem types, as the sequences of 10 decision problems of a given type are not conducted across the same Periods. To fix this, we define a new variable Instance as the number of times the subject has seen a decision problem of the current type in a given Period. For example, Instance will be equal to 1 the first time a subject sees a decision problem of type O_5A_5, 2 the second time, and so on, regardless of Period. Instance thus runs from 1 to 10 for each decision problem type.

Figure 3 plots average mistake rates in each instance subjects make decision for each type of decision problem. Since we randomized the order of 40 decision problems which include all four types of decisions, the horizontal axis captures the instance a decision problem occurred within that type of problem rather than the period of occurrence.

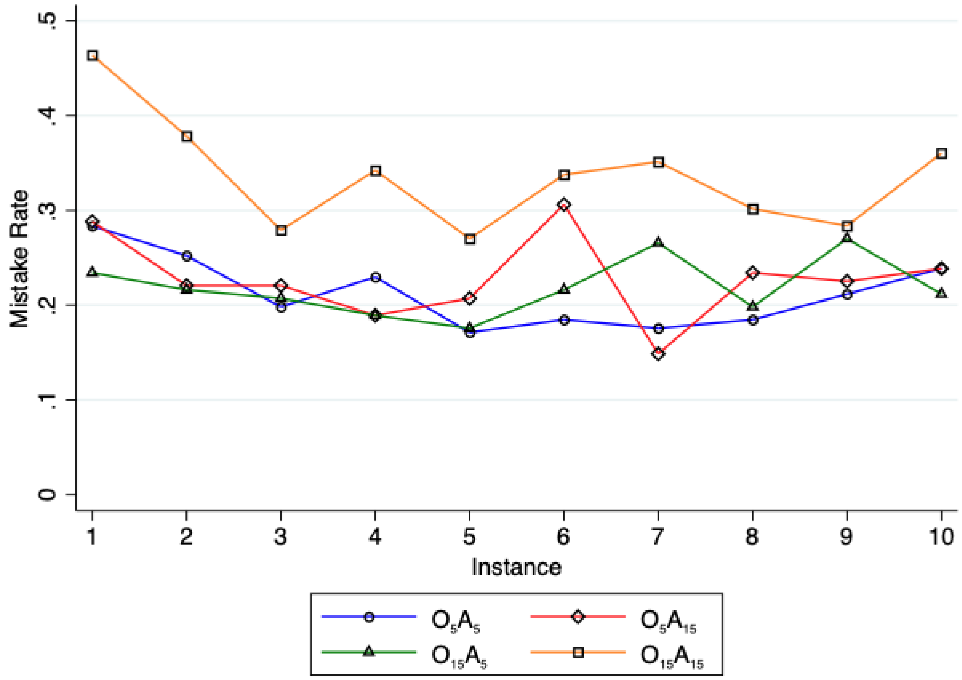


Figure 3: Mistake Rate by Decision Problem Instance

First, we can see from this graph that there is some degree of learning within decision problem type, but that this effect decreases somewhat over time, and appears to reverse in later instances. This is shown in the overall U-shape of this graph for each decision problem type and is in line with the regression results where coefficients of Period and Period^2 are negative and positive, respectively. We take this as evidence that the overall effect of learning would not undo our main result, had we only included more Periods and decision problems. Second, we take this graph to be additional evidence for our main result: the Mistake Rate is higher for $O_{15}A_{15}$ than for any other decision problem type for each Instance. This rules out the possibility that our main effect could have been the result of differential learning across decision problem types.

Appendix D Robustness Checks

For robustness, we conducted an additional six sessions of our main tasks under alternative designs. In this appendix, we present the relevant results used for robustness checks with this additional dataset.

D.1 Aggregate Results: 8 x 8

Table 28: Mistake Rates: Including Timeouts

	O_5	O_8
A_5		
Mean	0.168	0.160
Std Error	0.022	0.021
N	62	62
A_8		
Mean	0.131	0.242
Std Error	0.021	0.022
N	62	62

$p < 0.01$ for $O_5A_8 \to O_8A_8$, $O_8A_5 \to O_8A_8$, $O_5A_5 \to O_8A_8$
$p > 0.10$ otherwise

Table 29: Mistake Rates: Excluding Timeouts

	O_5	O_8
A_5		
Mean	0.159	0.147
Std Error	0.022	0.021
N	62	62
A_8		
Mean	0.108	0.223
Std Error	0.021	0.021
N	62	62

$p < 0.10$ for $O_8A_5 \to O_5A_8$
$p < 0.05$ for $O_5A_5 \to O_8A_8$ and $O_5A_5 \to O_5A_8$
$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_8 \to O_8A_8$
$p > 0.10$ otherwise

Table 30: Time: No Timeouts

	O_5	O_8
A_5		
Mean	48.935	49.586
Std Error	1.148	1.126
N	62	62
A_8		
Mean	51.754	55.345
Std Error	1.276	1.180
N	62	62

$p < 0.10$ for $O_5A_5 \to O_5A_8$

$p < 0.05$ for $O_5A_8 \to O_8A_8$

$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_5 \to O_8A_8$

Table 31: Time: Timeouts as Maximum Time

	O_5	O_8
A_5		
Mean	49.124	49.900
Std Error	1.165	1.141
N	62	62
A_8		
Mean	52.289	55.784
Std Error	1.266	1.180
N	62	62

$p < 0.05$ for $O_5A_8 \to O_8A_8$ and $O_5A_5 \to O_5A_8$

$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_5 \to O_8A_8$

Table 32: Time: Correct

	O_5	O_8
A_5		
Mean	48.733	49.209
Std Error	1.096	1.078
N	62	62
A_8		
Mean	51.904	54.914
Std Error	1.207	1.279
N	61	62

$p < 0.10$ for $O_8A_5 \to O_5A_8$

$p < 0.05$ for $O_5A_8 \to O_8A_8$ and $O_5A_5 \to O_5A_8$

$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_5 \to O_8A_8$

Table 33: Timeouts

	O_5	O_8
A_5		
Mean	0.010	0.015
Std Error	0.005	0.005
N	62	62
A_8		
Mean	0.024	0.026
Std Error	0.006	0.009
N	62	62

$p < 0.10$ for $O_5A_5 \rightarrow O_8A_8$

$p < 0.05$ for $O_5A_5 \rightarrow O_5A_8$

D.2 WTP

Table 34: Willingness to Pay: 8 x 8

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_8)$	$WTP(O\|A_8)$
Mean	3.100	2.800	3.219	2.562
Std Error	0.568	0.554	0.588	0.479
N	30	30	32	32

$p > 0.10$ for all relevant comparisons

Table 35: WTP Greater Than Zero: 8 x 8

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_8)$	$WTP(O\|A_8)$
Mean	0.633	0.600	0.656	0.625
Std Error	0.089	0.091	0.085	0.087
N	30	30	32	32

$p > 0.10$ for all relevant comparisons

D.3 Alt-High Noise Results

Table 36: Willingness to Pay: 15 x 15

	$WTP(O_{15}A_{15}) \rightarrow WTP(O_5A_5)$
Mean	5.452
Std Error	0.819
N	31

Excludes one observation where WTP = 70 ECU

Table 37: WTP Greater Than Zero

	$WTP(O_{15}A_{15}) \rightarrow WTP(O_5A_5)$
Mean	0.844
Std Error	0.065
N	32