Choosing to Have Less Choice

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Summary

This paper investigates choice between opportunity sets. I argue that individuals may prefer to have fewer options for two reasons: First, smaller choice sets may provide information and reduce the need for the agent to contemplate the alternatives. Second, contemplation costs may be increasing in the size of the choice set, making smaller sets more desirable even when they do not provide any information to the agent. I identify which of these reasons drives individual behavior in a laboratory experiment. I find strong support for both the information and cognitive overload arguments. The effects do not disappear as participants gain experience with the task. Applications of these results include firms' choices of product variety, as costs increase with the number of products offered, and the design of government policies, such as the Medicare Drug Discount Card Program, in which older citizens can choose among numerous cards for discounts in prescription drugs.

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Abstract

This paper investigates choice between opportunity sets. I argue that individuals may prefer to have fewer options for two reasons: First, smaller choice sets may provide information and reduce the need for the agent to contemplate the alternatives. Second, contemplation costs may be increasing in the size of the choice set, making smaller sets more desirable even when they do not provide any information to the agent. I identify which of these reasons drives individual behavior in a laboratory experiment. I find strong support for both the information and cognitive overload arguments. The effects do not disappear as participants gain experience with the task. Applications of these results include firms' choices of product variety, as costs increase with the number of products offered, and the design of government policies, such as the Medicare Drug Discount Card Program, in which older citizens can choose among numerous cards for discounts in prescription drugs.

"As a neophyte shoe salesman, I was told never to show customers more than three pairs of shoes. If they saw more, they would not be able to decide on any of them." Milton Waxman, shoe salesman.[1]

1 Introduction

Individuals often believe that more choices are better than less. This has been supported by research in economics and psychology. Firms sometimes seem to agree, and supply an increasing variety of products to consumers in an attempt to perfectly match their tastes. Recent evidence, however, suggests that increases in the number of options may decrease utility. In this paper, I conduct a laboratory experiment to investigate why this may be true. I study whether smaller sets are

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[1] "So Much Choice. How Do I Choose?": Letter to the editor. The New York Times, Jan 22, 2004.

preferred because they provide information about the ranking of the alternatives, or whether it is the decrease in the costs of processing information that make smaller sets more desirable.

In most of the economics literature, increasing the size of the choice set must weakly increase utility since the individual can always costlessly ignore part of the large set, and considering it can make him find a more desirable alternative. Research in psychology has also shown a positive relationship between the ability to choose (versus not being given this option) and intrinsic motivation (Deci, 1975, 1985), happiness (Taylor and Brown, 1988, Taylor, 1989) and a sense of control (Langer, 1975, Schulz and Hanusa 1978).

Recent papers, however, have shown that individuals are more likely to consume a product or enroll in a program when fewer options are available. Iyengar and Lepper (2000) show that sales of exotic jams increase when consumers are presented with a relatively small number of options (6) rather than a large number (24). They conclude that choice overload happens when more options are available, demotivating consumers. Similarly, Iyengar, Jiang and Huberman (2004) studied decisions of employees regarding whether to enroll in 401(k) retirement plans and found increases in participation in plans that offer fewer than 10 funds versus plans that offer 10 or more.

Bertrand et al (2005) quantify different psychological factors by examining take-up on loans offered though the mail to 60,000 clients by a lender in South Africa. To study the effect of overload on take-up, letters differed in the number of loans they described. They found that loan take-up increased 0.60 percentage points when fewer loans were described, the same effect as reducing the monthly interest rate by 2.3 percentage points[2]. Finally, Boatwright and Nunes (2001), show that removing low-selling items from supermarket shelves can increase aggregate sales by on average 11%.

A recent discussion in the media is concerned with the reasons for the low enrollment in the Medicare Prescription Drug Discount Card program, which started in June 2004 and ends in December 2005. Seniors who enroll can choose one of about 70 different cards (the number depends on the state of residency) and present the card at pharmacies for discounts of up to 25% on prescriptions. The card costs $30 or less (depending on the state) and about 4.7 million low-income Medicare recipients have the card paid for by the government and are eligible for a $600 subsidy in 2005 and 2006. Despite these benefits, in July 2005 only about 40% of the eligible low-income beneficiaries had enrolled in the program. Critics attributed this partly to the large number of cards available. Senator Kent Conrad of North Dakota introduced legislation in June 2004 to reduce the number of cards from about seventy to three for each region of the country. Conrad argued: "What I found is that people are confused. They are confused because there are so many cards." (Charleston Gazette, June 9, 2004). Learning when people prefer to have fewer options may help policy makers design programs and thus have important policy and welfare implications.

Understanding when people benefit from having fewer options is also important to firms, as the supply of product variety is a central decision. Several authors (Ravenscraft (1983), Bayus and Putsis (1999) and Draganska and Jain (2005)) have argued that costs of variety are convex

[2] The interest rates offered by the lender in the experiment were between 3.25% and 11.75% per month.

due to the complexity of the manufacturing process. Evidence suggests that increases in product line are associated with lower brand loyalty and worse relations with distributors and retailers. If consumers are better off with less variety, then firms can increase profits by reducing product lines. Some firms have realized these gains in strategy. During the first half of the 1990's, Proctor and Gamble cut its number of hair care products by almost half and increased market share by five percentage points. The president of the company, Durk I. Jager, said (Business Week, Sep 9th, 1996): "It's mind-boggling how difficult I've made it for them over the years." Identifying when people prefer to have fewer options may help firms make decisions regarding the supply of product variety.

In this paper, I conduct a laboratory experiment to investigate why individuals may prefer to have fewer options. I am concerned with situations in which individuals are initially uncertain about which is the best alternative for them in a choice set. To reduce this uncertainty, they can gather and process information, i.e., contemplate, which is costly in terms of effort and time. I consider two reasons for individuals to prefer fewer options: First, they may believe that a smaller set provides information about the ranking of alternatives, reducing necessary contemplation. I call this the value-of-information argument. Second, contemplation costs may be increasing in the size of the choice set, causing smaller sets to be more desirable than larger sets even when they don't provide any information to the agent. I say that such an individual has cognitive overload. I identify which of these reasons drives individual choice between sets in an experiment. This is the key contribution of this paper.

Value-of-information: An individual will prefer a smaller set if he believes it will provide him information about which alternatives he would choose, were he to engage in contemplation. Thus, fewer options are preferred if the individual trusts how the alternatives in the set were selected. In this case, a smaller set allows the individual to save contemplation costs.

Situations in which individuals prefer to restrict their choice sets because they believe a selection mechanism can help them make a better decision occur frequently in practice. For example, we invest money in mutual funds trusting that analysts have done a good job of gathering and processing information about stocks, so we don't have to incur these costs. We take recommendations of friends and magazines regarding restaurants because we trust their selection criteria and want to save time gathering this information ourselves. More generally, one can delegate a decision to someone we fully trust to save the costs of gathering and processing information. The idea that choice sets provide information about the ranking of alternatives has been suggested by Luce and Raiffa (1957) and McFadden (1999), and is related to the literature on herding and imitation, such as Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992).

Under the value-of-information argument, a smaller set whose alternatives are randomly selected from a larger set should never be preferred because random selection does not provide the agent with any information. In fact, the individual can replicate the random selection himself when given a larger set by randomly ignoring extra alternatives, and considering them may increase his utility. This fact will be important to identify the effect of value-of-information in the experiment.

Cognitive overload: The cognitive overload argument posits that fewer options may be preferred if contemplation costs are increasing in the size of the choice set. This happens if individuals do not ignore some options when faced with larger sets, but instead gather and process more information as the set increases. This behavior is consistent with the use of heuristics that necessarily consider a larger number of alternatives when more options are available, such as sequentially eliminating the worst option. If there is a fixed cost of each elimination, contemplation costs will increase with set size. In these situations, an individual will prefer smaller sets if decision costs increase more than the benefits with the expansion of the choice set. One implication is that fewer alternatives may be preferred even if they are a random selection from a larger set. This difference from the value-of-information allows me to contrast the two different explanations in the experiment. The idea that consumers can become overwhelmed by "too much choice" has been suggested by Jacoby (1984), Huffman and Kahn (1998) and Iyengar and Lepper (2000)[3].

There are other reasons why individuals may prefer to have fewer options. For example, utility may by affected by anticipated feelings of regret and rejoice in decisions under uncertainty, as argued by Loomes and Sudgen (1982). I will discuss how giving feedback to induce anticipated regret affects choice of sets in the experiment.

Gul and Pesendorfer (2001) show that smaller opportunity sets may be preferred in the presence of temptation. For example, a person on a diet may not buy chocolates to avoid the temptation of eating chocolates in the future. In games such as a two player prisoner's dilemma, having fewer actions can make agents better off by excluding the Pareto dominated outcome. In decisions under ambiguity, Manski (2000) shows that increasing the choice set may also reduce welfare because an ex-ante undominated action may turn out to be dominated when ambiguity is resolved. Although important, I do not focus on these arguments because they do not seem central to explain the empirical problems I am concerned with in this paper.

The experiments

In view of the theoretical explanations discussed above, I investigate why individuals may prefer to have fewer options in a laboratory experiment. In particular, if people choose to restrict their choice sets, is it because of the value-of-information or cognition overload? Alternatively, are individual choices consistent with the assumption that more options are always weakly preferred?

Participants went through the following two-stage decision in several circumstances: First, they were asked to choose between sets of lotteries in which one set was a subset of the other. Participants could see the large set but not the small one. Instead, they were given information about how the lotteries in the small set were selected from the large set. After they chose the set, they could see it and choose one lottery from it.

[3] The presence of contemplation costs alone is not sufficient for individuals to prefer fewer options. Ergin (2003) proves a representation theorem for preferences in which the utility function derived incorporates contemplation costs that can be used to reduce uncertainty. His key axiom is monotonicity; that is, more options are weakly preferred by the agent. Therefore, he implicitly assumes that individuals can ignore extra alternatives as their choice set increases in size. When this is true, individuals contemplate only when doing so increases benefits more than costs.

In the first round, the small set was selected randomly from the large set. Second, it was chosen by 10 graduate students in economics and Kellogg, with the 5 lotteries chosen most often comprising the small set. In the third round, the small set included the only 5 undominated lotteries in the large set.

By varying how the alternatives in the subsets were selected and making participants aware of this, identification between value-of-information and cognitive overload is possible. According to value-of-information, an individual should never choose the small set under random selection, and should always choose the small set of undominated lotteries. Moreover, choice of the set selected by graduate students should be accompanied by choice of the set of undominated lotteries. On the other hand, choice of the randomly selected set is consistent with cognitive overload. In this case, it should be accompanied by choice of the small sets in the other two selection methods. Finally, if more is always weakly better than less, the small set should either not be selected or be selected only when it contained the undominated lotteries.

Next, I study how decisions changed when participants received feedback regarding their choices of lotteries. Although feedback was given after decisions were made, participants knew in advance that they would receive it. Thus, if anticipated feedback affects utility, such as through regret, participants' choices may change relative to rounds without feedback.

I also investigate how choice between sets changes when individuals face a given large set repeatedly. The question is whether experience reduces uncertainty about what the best option is and increases the proportion of participants choosing the large set, especially in the cases of random and student selection. Alternatively, participants could become aware of the difficulty in the decision and switch to small sets, especially in the cases of student and undominated selection. No feedback was given after choices were made, and this was known in advance.

The experiment was conducted with two groups of participants. Group 1 chose between sets of 25 lotteries and subsets of 5, while Group 2 chose between sets of 50 and subsets of 5. All large sets had 5 lotteries that were not strictly dominated by any other. I study how the importance of cognitive overload and value-of-information in explaining choice between sets depends on the size of the large set.

I now describe the main results of the experiment. I found that 32% of participants in Group 1 (large set with 25 lotteries) and 48% of participants in Group 2 (large set with 50 lotteries) chose the small set under random selection in round one, consistent with cognitive overload. When selection was done by graduate students, 71% of participants chose the small set in Group 1 and 72% chose the small set in Group 2, consistent with value-of-information and cognitive overload. When the small set consisted of all undominated lotteries, it was chosen by 80% of Group 1 participants and 74% of Group 2 participants. This is consistent with some proportion of participants having zero or very low contemplation costs. I also found that most participants who chose the small set under random selection also did so in the other two conditions, and those who chose the small set under graduate students' selection but not in random selection also chose the small set of undominated lotteries. This is consistent with the predictions from cognitive overload and value-of-information.

When participants were given feedback, the proportion of small sets chosen under random selection decreased to 13% in Group 1 and 22% in Group 2. This suggests that participants were aware that randomly selected sets would likely have worse lotteries, and anticipated negative feedback when choosing this set. Moreover, this negative feedback reduced utility from the random sets and affected decisions, possibly due to anticipated regret. The effect of feedback on choice under the other selection mechanisms was negligible, suggesting they did not expect negative feedback in those cases.

When the large set was repeated to study the effect of experience, the randomly selected sets were chosen on average by 18% of participants in Group 1 and 31% of participants in Group 2, and there was a statistically significant positive trend for Group 2. This is a considerable increase relative to when feedback was given. When sets were selected by graduate students, it was chosen on average by 77% of participants in Group 1 and 70% in Group 2, again with a statistically significant positive trend for Group 2. This suggests that experience with the large set made participants aware of the difficulty of the decision in Group 2, generating a switch to the small set. Choice of the sets of undominated lotteries was not affected by experience, remaining around 75% for both Groups. Thus, I find that participants show a preference for fewer options which remains constant or even increases over time (Group 2).

The pooled data over rounds shows that men are more likely to choose a large set than women. In addition, more risk-averse participants (elicited using a Holt and Loury, 2002, procedure) were less likely to choose the randomly selected small sets, but were more likely to choose the small sets in the other selection methods.

In another experiment, participants were given the sets of lotteries and asked to choose one lottery from each set. Thus, they did not choose between sets. I study whether self selection into large sets is related to higher ability, or alternatively, whether participants choosing large sets were too optimistic about their ability, and made worse decisions on average. I find that participants who chose the large sets more times were also more likely than average to choose undominated lotteries from them. Therefore, choice of large sets is positively related to ability. Those with below average ability, on the contrary, often preferred to have their decisions restricted by other selection mechanisms, even if this mechanism was random and could potentially be replicated by themselves. This is consistent with some individuals having cognitive overload, in particular those that are relatively worse than average in choosing from large sets.

The rest of the paper is organized as follows: The next section discusses the theoretical arguments for why agents may prefer smaller sets. Section 3 describes the experimental design, Section 4 discusses the results, Section 5 shows the debriefing to some questions the participants answered and Section 6 concludes the paper.

2 Theoretical Explanations

2.1 Value-of-Information

Consider an individual choosing one alternative from a set. Assume he has not gathered information about the alternatives, or has not processed his information. As a result, he is uncertain about the ranking of the alternatives, and does not know which one is best for him. Assume this uncertainty can be eliminated by gathering and processing information, i.e., contemplating, which is costly. Contemplation can be interpreted as the effort and time spent in making the decision. The individual chooses the amount of contemplation. If he chooses not to contemplate, these costs equal zero. The more he contemplates, the higher the cost, but the lower the uncertainty when selecting an alternative from the choice set. Therefore, first the amount of contemplation is chosen, and then one alternative is selected taking into account the information gathered and processed through contemplation.

An individual may prefer a subset of a larger set, depending on his beliefs regarding how these options were selected. If he trusts the mechanism that selects the alternatives, he may prefer the smaller set since it allows him to save the costs of contemplation. However, if an individual believes the small set contains a relatively bad selection, the large set will be preferred, even if contemplation costs incurred are higher. Thus, a smaller set will be preferred when it is believed to provide information about the ranking of the alternatives that otherwise would have to be acquired through costly contemplation. This is the value-of-information argument. For example, an individual may prefer a small set selected by an expert who has incurred the contemplation costs if he believes the expert and himself have similar tastes. Thus, a set with one alternative may be preferred to any larger set if it is believed to contain exactly the alternative which would be chosen if the individual were to contemplate from the larger set. With only one alternative, the individual will not need to contemplate. A model of decision under uncertainty that formalizes the value-of-information argument is developed in Appendix A.

If a smaller set is believed to have alternatives that are randomly selected from a larger set, then the latter will always be preferred because random selection does not provide the individual with any information about the ranking of alternatives. In fact, the individual can replicate the smaller set himself by randomly ignoring some alternatives at no cost, and considering them may increase his utility. Therefore, as long as individuals are able to ignore extra alternatives, fewer alternatives that are randomly selected from a larger set will never be preferred.

The assumption of costly contemplation is important. If contemplation were costless, an individual would be able to achieve full information by contemplating sufficiently. Thus, smaller sets only restrict the individual and more options are always weakly preferred. This is the traditional framework without bounded rationality or information acquisition costs, in which more options are always weakly better than fewer options.

2.2 Cognitive overload

I now discuss a second explanation for why an individual may prefer to have fewer options. Again, consider an individual choosing one alternative from a set, who is uncertain about which option is best for him. Uncertainty can be reduced by contemplation, which is costly. I now assume an individual does not ignore extra alternatives when faced with an increasing number of choices. Instead, he increases the amount of contemplation as the set increases. I say that this individual has cognitive overload. In this case, he will prefer fewer options if the benefits of increasing the choice set are smaller than the resulting increase in contemplation costs.

Research on individual decision making has argued that individuals use heuristics that consider a larger number of alternatives as the set increases, such as sequentially eliminating the worst option. If there is a fixed cost of each elimination, then contemplation costs increase as the set increases. For example, in Tversky's (1972) "elimination by aspects" model, each alternative is viewed as a set of aspects and individuals reduce the number of alternatives by requiring each aspect to be greater than some threshold value. Similarly, Russo and Dosher (1983) argue that people select the alternative that is best on the largest number of attributes. Furthermore, they eliminate the attribute whose difference between alternatives is smallest, and then select the alternative with a clear advantage on the other attributes. In this case, the larger the choice set, the greater the number of comparisons that must be made, and if there is a fixed cost of each comparison, cognitive overload occurs. Tversky et al. (1988) suggest the following choice strategy: First, individuals check for dominating alternatives. Second, they determine whether some alternatives have a clear advantage over the others based on differences in their attributes. Third, ties are resolved by selecting the alternative that is best according to the most important attribute. That is, a lexicographic rule is used. Again, this heuristic is consistent with contemplation costs that increase with set size if there is a cost to making each binary comparison.

Research has also shown that set size affects the decision-making process by inducing individuals to switch to simpler heuristics (Payne, 1982; Timmermans, 1993; Wright, 1975). Timmermans (1993) found that 21% of the people who faced 3 alternatives used an elimination strategy, and this number increased to 31% of those facing six alternatives and to 77% of those facing nine. This was accompanied by a decrease in the amount of information used, measured by the number of attributes considered about each alternative.

Not all heuristics predict that smaller sets will be preferred when costs of processing information exist. Simon (1956) argues that boundedly rational individuals use satisficing strategies. They choose the first alternative encountered that gives them a minimum level of utility, ignoring the other alternatives. In this case, larger choice sets are preferred as they increase the likelihood of reaching the threshold value. As Simon (1997) argues, this strategy will only be used if search costs are independent of the size and complexity of the task.

3 Experimental Design

I now describe the experiment used to study individual choice between opportunity sets. The main objective is to identify behavior with either of the two arguments previously discussed, or with preference for more options. Instructions can be found in Appendix B.

The experiment was conducted in the Kellogg Behavioral Laboratory at Northwestern University during Spring 2005. Participants spent between 20 and 60 minutes and earned an average of $12.50. The experiment was run on a computer using the software MediaLab. Subjects were recruited by sending e-mail invitations to the assistants of each department in the Weinberg College of Arts and Sciences, School of Communications, McCormick School of Engineering and Medill School of Journalism. The assistants were asked to forward the invitation to all students in their department. As a result, 232 students participated in the experiment. The characteristics of the subject pool are summarized in Table 1.

Total	232 participants
Age	min = 17; max = 35; median = 20
Gender	female = 0.64; male = 0.36
Field*	biology = 0.14; economics = 0.25; eng, math or stats = 0.21; language or journalism = 0.35; psych = 0.09; other social science = 0.34
Class	freshman = 0.26; sophomore = 0.24; junior = 0.20; senior = 0.25; grad = 0.05
Stats	none = 0.31; high school = 0.14; undergrad beg = 0.34; undergrad interm = 0.14; graduate = 0.03
Econ	none = 0.32; undergrad beg = 0.46; undergrad interm = 0.22; grad = 0

*Students were allowed to choose more than one field of study

Table 1: Characteristics of subject pool

There were two treatments in which participants made decisions involving lotteries. Treatment 1 investigates whether participants preferred a subset of a larger set, and if so, whether behavior is consistent with value-of-information or cognitive overload. Participants first chose between sets of lotteries and then selected one lottery from the chosen set. Treatment 2 studies whether participants who chose the large sets most often in treatment 1 self-selected themselves due to higher ability, or alternatively, due to over-optimism regarding their ability, and actually made worse decisions on average. Thus, while participants were choosing between sets in treatment 1, they were assigned the sets in treatment 2. Different people participated in treatments 1 and 2. Details of each treatment are explained in the next section.

Each treatment had two groups of participants. Group 1 made choices involving sets of 5 and 25 lotteries, while Group 2 made choices involving sets of 5 and 50 lotteries. Research on cognitive overload suggests individuals are able to optimally process at most six alternatives (Bettman (1979), Malhotra (1982), Wright (1975)). Thus the choice of 5 lotteries in the small sets. Each of the large sets had 5 lotteries that were not strictly dominated by any other. In addition, the sets of 50 in Group 2 were generated by adding 25 dominated lotteries to each set of 25 in treatment 1. Thus, the large sets of Group 2 contained the large sets of Group 1. The usefulness of including dominated lotteries is that it allows decisions to be ranked, facilitating the analysis of individual choices.

Lotteries paid integer amounts between \$3 and \$17, and varied in expected values and variances. Most sets also contained dominated lotteries. Therefore, choice required making calculations to determine which lotteries were undominated and/or thinking about the trade-offs between central tendencies and spreads. Thus, reducing uncertainty about which lottery to select required contemplation, which is the assumption in value-of-information and cognitive overload.

I used a Holt and Laury (2002) procedure to estimate individual levels of risk aversion. Participants made 10 choices between 2 lotteries, depicted in Table 2. The crossover point to the high-risk lottery can be used to estimate individuals' degree of risk aversion if a constant relative risk aversion utility function is assumed, i.e., if $u(x) = x^{1-r}/(1-r)$, where r is the coefficient of relative risk aversion. With this utility function, an individual is risk loving if $r < 0$, risk neutral if $r = 0$, and risk averse if $r > 0$. The payoffs of the lotteries were selected to be the same order of magnitude as the lotteries in Part 1, since risk attitudes may vary with the size of payoffs. For the lotteries used, the risk neutral individual should select 4 safe lotteries followed by 6 risky lotteries, which coincides with the optimal choices of an individual with $r \in (-0.11, 0.24)$.

	Option 1		**Option 2**		
	\$12	**\$6**	**\$16**	**\$3**	**Expected Payoff**
Round	**Prob**	**Prob**	**Prob**	**Prob**	**Difference**
1	0.1	0.9	0.1	0.9	2.30
2	0.2	0.8	0.2	0.8	1.60
3	0.3	0.7	0.3	0.7	0.90
4	0.4	0.6	0.4	0.6	0.20
5	0.5	0.5	0.5	0.5	-0.50
6	0.6	0.4	0.6	0.4	-1.20
7	0.7	0.3	0.7	0.3	-1.90
8	0.8	0.2	0.8	0.2	-2.60
9	0.9	0.1	0.9	0.1	-3.30
10	1	0	1	0	-4.00

Table 2: Holt and Laury procedure to elicit risk aversion

Participants then answered questions about their strategies throughout the experiment, as well as on their demographics. Finally, payments were made in private according the result of one lottery, plus a \$4 participation fee. The lottery was randomly selected from those chosen in the Holt and Laury procedure with probability 0.1, and otherwise with probability 0.9 by having participants roll

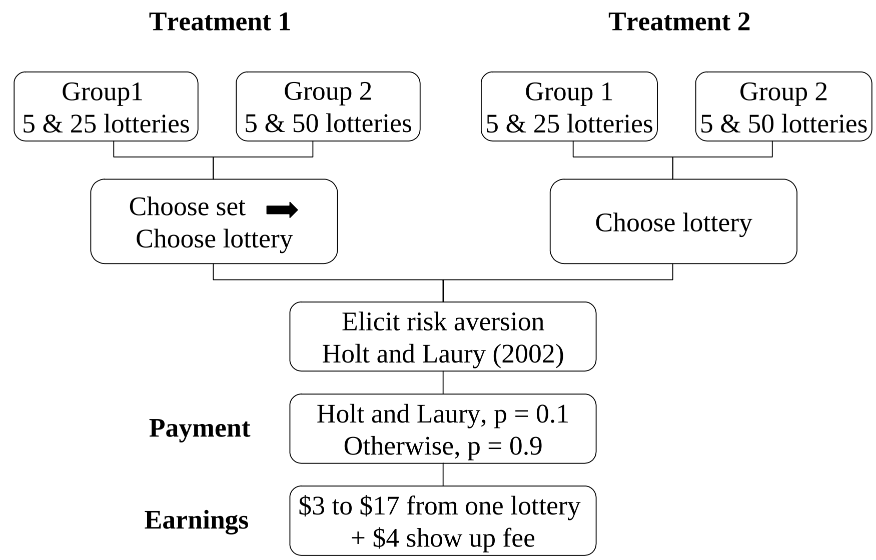

Figure 1: Overview of experimental design.

a 10 sided die. The Holt and Laury procedure was easier and shorter, and therefore less weight was given to it. One lottery was then selected by rolling dice and the 10 sided die was rolled again to determine the payoff from the lottery. Participants were made aware of the payment method at the beginning of the experiment. They could leave as soon as they finished. Details of each treatment are presented next, followed by a discussion of the main findings. Figure 1 gives an overview of the experimental design just described.

3.1 Treatment 1

I now describe treatment 1 in detail. The objective is to study whether participants were willing to choose a smaller set over a larger one that contains it, and if so, to see whether this was due to value-of-information or cognitive overload. There were 110 participants in this treatment, with 56 in Group 1 (large set with 25 lotteries) and 54 in Group 2 (large set with 50 lotteries). Recall that all small sets had 5 lotteries each.

There were 24 rounds in which participants went through several two-stage decisions in which they first chose between two sets of lotteries, small and large, and then selected one lottery from the chosen set. In each round, participants could see the large set of lotteries (with 25 or 50 alternatives) and asked to choose between this set and a subset of 5 lotteries, which they could not see. Instead, they were given information about how the lotteries in the small set were selected from the large set. After choosing a set, participants could see it. They then selected one lottery from this set. Participants were asked to choose between: (a) the small set selected according to the information given, or (b) the large group which contained the small one. The exact wording of the information given to Group 1 is shown below. The wording for Group 2 is the same with "25" replaced by "50".

1. "This group of 5 lottery tickets was randomly selected from the group of 25 shown in (b). This was done by having a computer program randomly select 5 numbers from 1 to 25, corresponding to the 5 lotteries. If you want more details about how this was done, or what computer program was used, please ask the experimenter."

2. "This group of 5 lotteries was selected from the group of 25 in (b) by 10 economics and Kellogg graduate students. These students have extensive training in statistics, and solve these kinds of problems all the time. Here are some details: 10 students were given the set of 25 lotteries in (b) and asked to choose the 5 within the group which they thought were the best. This group contains 5 of the lotteries most frequently chosen by these 10 econ and Kellogg graduate students. If you need more details on this procedure or if you want to know more about who are the graduate students involved, please ask the experimenter."

3. "This group of 5 lottery tickets was selected by taking the 5 best lotteries in the group of 25 shown in (b). This means that the lotteries in the small group will give you at least the same amount of money as the lotteries in the large group, and possibly more. Alternatively, for each lottery in the large group, there is a lottery in the small group that will give you at least the same amount of money, and possibly more."

Rounds 1 through 3 consisted of giving participants the two-stage decision previously described. Large sets were different in each round. In round 1, participants chose between the small set under random selection and a large set. In round 2, they chose between the small set selected by graduate students and a large set. In round 3, choice was between the set of undominated lotteries and a large set.

By varying how the alternatives in the subsets were selected and making participants aware of this, identification between value-of-information and cognitive overload is possible. According to the value-of-information argument, participants should never choose the small set under random selection (round 1) because it does not provide any information about the ranking of the alternatives. Moreover it could be replicated by randomly ignoring alternatives in the large set. However, the small set should always be chosen when it contains the best lotteries (round 3), since it allows participants to save the contemplation costs of eliminating dominated lotteries. Choice of the small set under random selection is, however, consistent with cognitive overload if contemplation costs from the large set are larger than its benefits. In this case, choice of the small set under random selection should be accompanied by choice of the small set in the other two selection mechanisms, since information should not play a role in the decisions. Finally, if more is always weakly better than less, the small set should either not be selected or be selected only when it contained the undominated lotteries.

In rounds 4 through 6, I study how decisions changed when participants received feedback regarding their choices of lotteries. As before, participants made choices between small and large

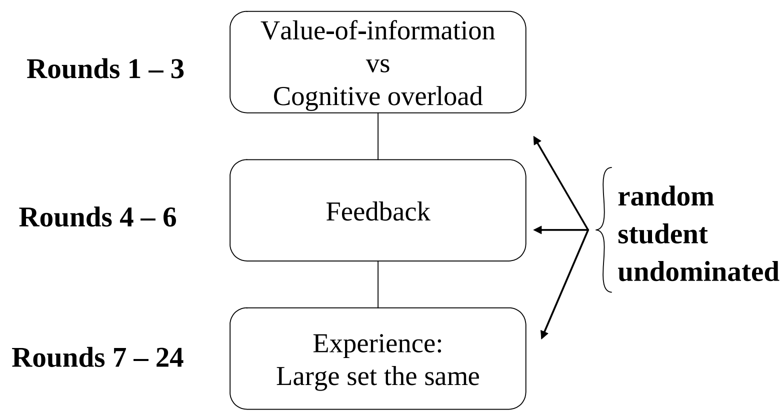

Figure 2: The figure gives an overview of treatment 1. In each round, participants first chose between sets of lotteries. Then, the chose one lottery from the set they selected.

sets without initially seeing the small sets, but instead receiving information about how they were selected. After choosing the set, they selected one lottery from it. The order in which the small sets were given was the same as in rounds 1-3, namely random selection, followed by student selection and lastly undominated set. Although feedback was given after the choices were made, participants knew in advance that they would receive it. Thus, any effect of anticipated feedback on choices, due for example to regret, should be reflected in changes in behavior relative the previous rounds, in which no feedback was given.

In rounds 7 through 24, I study choice between sets when individuals face the same large set repeatedly. The question is whether experience reduces uncertainty about what the best option is and increases the proportion of participants choosing the large set, especially in the cases of random and student selection. Alternatively, participants could become aware of the difficulty in the decision and switch to small sets, especially in the cases of student and undominated selection. Participants went through the two-stage decision previously described. To study the effect of experience, large sets were the same for all 18 rounds, and so were the small sets selected by graduate students and the sets of undominated lotteries. The sets of small sets randomly selected varied. To decrease predictability, the order in which pairs of sets were presented varied arbitrarily, and can be found in the instructions in appendix B. Participants were not told in advance of the number of rounds or that large sets remained the same. No feedback was given after choices were made, and this was known in advance. An overview of the treatment 1 is depicted in figure 2.

Figures 3-5 show the range of expected values of the lotteries given to participants. The 24 rounds are divided into 3 figures of 8 rounds each, one for each of the three sampling methods. The vertical lines give the range of expected values of the lotteries in large sets, and the vertical boxes give the range of expected values of lotteries in the small sets. Recall that large sets were the same in the learning rounds, corresponding to numbers 3-6 in the figures, as were small sets selected by graduate students and those consisting of undominated lotteries.

Observe that the random selection reduces considerably the maximum amount that can be earned in some of the rounds. In addition, the range of expected values is relatively large. Thus if an individual does not like the highest expected value lottery because, for example, its variance is so large, he might have to settle for a much lower expected value and less risky alternative. This is not true in the other two conditions. Graduate students tended to choose very safe lotteries with expected values around \$8.5. The sets chosen by graduate students were similar to the undominated sets in treatment 1, but tended to have lotteries with lower variance in treatment 2. The undominated lotteries had expected values between \$8 and \$9.6.

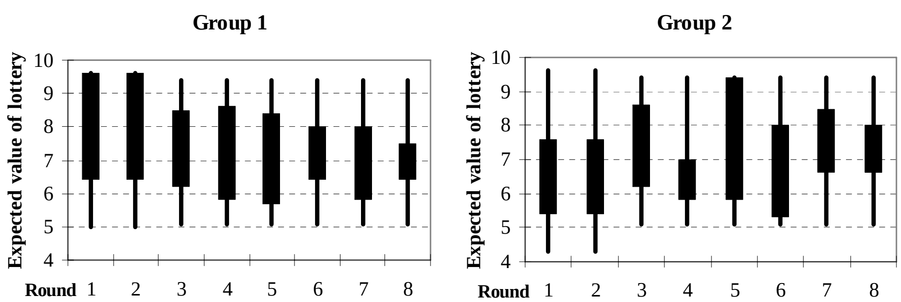

Figure 3: Random selection: Vertical lines give the range of expected values of lotteries in large sets, and vertical boxes give range of small-random sets.

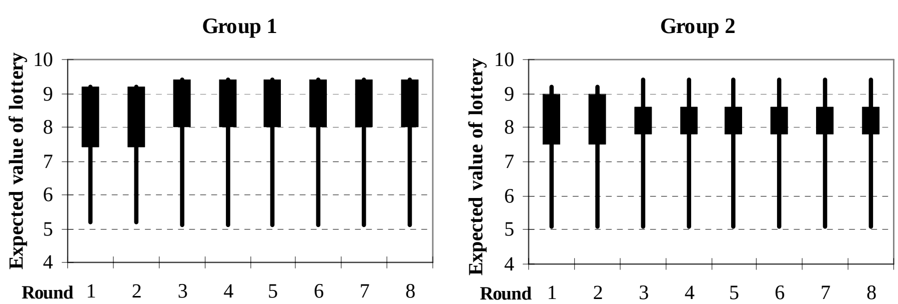

Figure 4: Student selection: Vertical lines give the range of expected values of lotteries in large sets, and vertical boxes give range of small-student sets.

Participants then went through the Holt and Laury (2002) procedure to elicit risk-aversion, answered the questionnaire and payments were made according to the rule previously described.

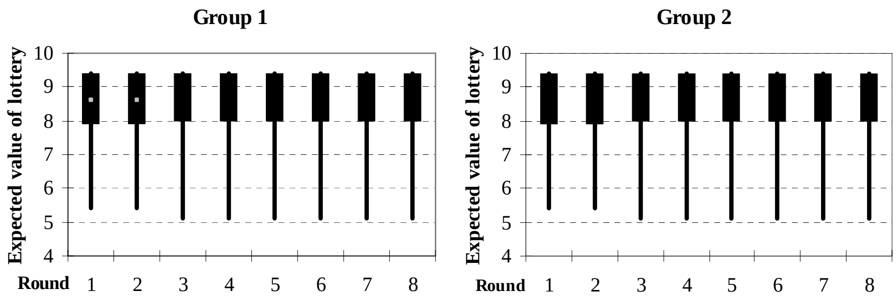

Figure 5: Undominated selection: Vertical lines give the range of expected values of lotteries in large sets, and vertical boxes give range of small-best sets.

3.2 Treatment 2

In treatment 2, participants were given the sets of lotteries of treatment 1 and asked to choose one lottery from each of these sets. Thus, participants did not choose between sets in treatment 2. By comparing the choice of lotteries when sets are endogenous and exogenous, it is possible to investigate whether subjects choosing the large sets in treatment 1 were self-selected into this condition because of higher ability, or alternatively, whether they were too optimistic about their ability and actually made worse decisions on average relative to a person in treatment 2.

There were 122 participants in this treatment, with 61 in Group 1 (large sets with 25 lotteries) and 61 in Group 2 (large sets with 50 lotteries). People participating in treatment 2 were different than those participating in treatment 1.

Participants were asked to choose one lottery from each of the sets presented to them. There were two conditions, which varied according to the order in which the small and large sets were presented. In the first condition, subjects were given the small sets first, in the order a subject in treatment 1 would face had he chosen all the small sets. Then, all the large sets were given, in the order a subject in treatment 1 would face had he chosen all the large sets. This condition had 30 participants in Group 1 and 32 subjects in Group 2. The second condition consisted of giving subjects the large sets first, followed by the small sets, again in the order consistent with treatment 1. There were 31 participants in Group 1 and 29 participants in Group 2. Note that participants in treatment 1 chose a lottery from *either* the small or large set in each round. Thus, participants in treatment 2 made twice as many choices of lotteries. This can generate large differences in learning between treatments 1 and 2 and this is the reason for introducing the two conditions. No information was given to participants regarding how the lotteries in the sets were selected. Figure 6 summarizes the design of treatment 2.

Feedback was given regarding whether participants chose a dominated lottery from the same sets in which participants in treatment 1 received feedback. Again, they were told in advance that they would receive feedback. Feedback was given to make choices in treatment 2 comparable to those of treatment 1.

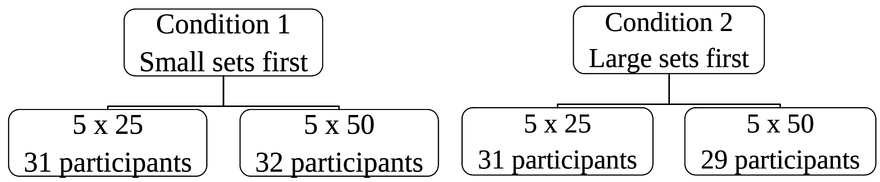

Figure 6: Overview of treatment 2.

Participants then went through the Holt and Laury (2002) procedure to elicit risk-aversion, answered the questionnaire and payments were made according to the rule previously described.

4 Experimental Results

4.1 Treatment 1

4.1.1 Choice of sets with no feedback: Rounds 1 - 3

Table 3 shows the proportion of small sets chosen in rounds 1 through 3. In round 1, when the lotteries in the small sets were randomly selected from the large set, 32% of participants in Group 1 (in which participants chose between sets of 25 lotteries and subsets of 5 lotteries) chose the small set. This number increased to 48% in Group 2, in which participants chose between sets of 50 lotteries and subsets of 5 lotteries. A one-sided t-test rejects the null hypothesis that these numbers are the same against the alternative that the latter is greater than the former with p-value $= 0.059$ ($t = 1.56$).

The large proportion of participants who chose the small set in round 1 shows that cognitive overload is an important explanation for why individuals prefer to have fewer options. As discussed previously, the value-of-information argument predicts that randomly selected small sets should never be chosen, since they do not provide any information and can potentially be replicated by an individual facing the large set. However, according to the cognitive overload hypothesis, the randomly selected small sets should be chosen if the contemplation costs incurred with the large set are sufficiently large. That cognitive overload exists and is important is also supported by the increase in the proportion of participants who chose the small randomly selected set in Group 2 relative to Group 1. This suggests that to avoid the increasing costs of contemplation as the number of alternatives in the large set increases, participants preferred to choose the small set. Section 5 presents several of the answers participants provided regarding their strategies for choosing between sets of lotteries, and shows how some of them are clearly consistent with cognitive overload.

Table 3 also shows that 71% of participants in Group 1 and 72% of participants in Group 2 chose the small set when the lotteries were selected by economics and Kellogg graduate students. A t-test cannot reject the equality of these numbers with p-value $= 0.50$ ($t = 0.00$). The increase in these numbers relative to the proportion of participants who chose the small set under random selection indicates the importance of the value-of-information argument in explaining why individuals prefer to have fewer options. It is consistent with participants placing a high probability of receiving a set containing sufficiently good lotteries under the graduate students' selection due to the information provided by the set. Note, however, that generally the small sets selected by graduate students were not identical to the sets of undominated lotteries, as can be seen from figures 4 and 5, especially in Group 2. Thus, most participants preferred to incur a cost in terms of monetary payoffs to save the contemplation costs of making a choice from the large set. Section 5 shows that the answers to the debriefing questions are consistent with the value-of-information argument.

Finally, the last two columns of table 3 show that 80% of participants in Group 1 and 74% in Group 2 chose the small sets when they contained the undominated lotteries. The equality of these numbers cannot be rejected by a one-sided t-test with p-value = 0.18 ($t = 0.94$). Choice of the large set by part of the participants is consistent with zero or very low contemplation costs, due for example to high ability. Section 5 shows that the answers to the debriefing questions are consistent with the value-of-information argument.

	5 x 25	**5 x 50**	**T-test**
Random	0.32	0.48	-1.59*
Student	0.71	0.72	0.00
Undominated	0.80	0.74	0.94

*P-value=0.059

Table 3: Proportion of small sets chosen in rounds 1 - 3 in Group 1 (5x25) and Group 2 (5x50).

Table 4 shows the proportion of participants who chose a small set in one of the three rounds conditional on choosing a small set in another of the three rounds. The numbers are similar to the unconditional proportions shown in table 3. The cognitive overload argument predicts that when an individual chooses the small set under random selection, he also chooses a small set under the student and undominated selections. Table 4 shows that this is true, i.e., those that chose the randomly selected small set usually (over 70% of them) chose the small sets under the other two selection methods. The value-of-information argument predicts that participants who choose the small set selected by the graduate students also choose the small set of undominated lotteries. This is supported by the data, with 88% doing so in Group 1 and 77% doing so in Group 2.

I classify participants into three types. A cognitive overload type is someone who chose the small set in the three rounds, regardless of the selection method. A value-of-information type is a participant who chose the small set in rounds when it was selected by graduate students and when it contained the undominated lotteries, but not when it was a random selection from the large set. Finally, a more is better type is an individual who either did not choose the small set at all or did so only when it contained the undominated lotteries. This classification is a way to determine the

	5 x 25	5 x 50
P(undom|random)	0.89 (18)	0.88 (26)
P(student|random)	0.72 (18)	0.73 (26)
P(random|student)	0.33 (40)	0.49 (39)
P(undom|student)	0.88 (40)	0.77 (39)
P(student|undom)	0.78 (45)	0.75 (40)
P(random|undom)	0.36 (45)	0.58 (40)

*In parenthesis is number of observations

Table 4: Proportion of participants who chose one small set conditional on having chosen another. Rounds 1 - 3.

relative importance of value-of-information and cognitive overload in explaining why participants chose the small sets. Table 5 shows the proportion of people of each type.

Among participants who chose between sets of 5 and 25 lotteries, 20% were classified as cognitive overload types, 43% as value-of-information types and 19% as more is better types. This can explain 82% of behavior in the experiment. Of participants who chose between sets of 5 and 50 lotteries, 33% were classified as cognitive overload types, 22% as value-of-information types and 15% as more is better types, explaining 70% of behavior. Thus, the share of cognitive overload types increased considerably from Group 1 to Group 2, while the share of value-of-information types decreased to about half. The share of more is better types also decreased. The data is consistent with cognitive overload becoming relatively more important than value-of-information to explain preference for fewer options as the size of the choice set increases. This suggests the use of heuristics that necessarily consider more alternatives as more options are available. In both groups, the share of participants classified as more is better types is considerably lower than those who prefer fewer options (19% vs 63% in Group 1 and 15% vs 55% in Group 2). This surprising in view of the extensive amount of literature in economics and psychology that assumes individuals prefer to have more options.

	5 x 25	5 x 50
Cognitive Overload	0.20	0.33
Value-of-information	0.43	0.22
More is Better	0.19	0.15
Sum All	0.82	0.70

Table 5: Classification by types: Rounds 1 - 3. A cognitive overload type is a participant who chose the small sets regardless of the selection method. A value-of-information type is a participant who did not choose the small set under random selection, but did so in the student and undominated selection. A more is better type either did not choose the small set or did so only when it contained the undominated lotteries.

In contrast to the growing literature which suggests that people sometimes prefer to have fewer options, this paper's contribution is to identify in an experiment the reasons why this may be true. The experimental results are consistent with people willing to restrict their choice sets to save in contemplation costs, i.e. the costs of gathering and processing information. Part of the participants did so only when the small sets were seen as providing information about the ranking of the alternatives, as in the student and undominated selection, but when the alternatives in the small set were a random selection from the large set, they preferred the large set. This suggests that they believed the random set could be replicated by ignoring some alternatives. On the other hand, part of the participants chose the small sets regardless of the selection method. This is consistent with contemplation costs that increase as the choice set increases, i.e., with cognitive overload.

4.1.2 Feedback: Rounds 4 - 6

Rounds 4 - 6 study whether feedback regarding choice of lotteries affects individual choices of sets. Although feedback was given after decisions were made, participants knew in advance that they would receive it. Thus, if anticipated feedback affects utility, such as through regret, participants' choices may change relative to rounds without feedback.

Table 6 shows the proportion of small sets chosen in rounds 4 - 6. In round 4, when selection was random, 13% of participants in Group 1 and 22% of participants in Group 2 chose the small set. A one-sided t-test rejects the null hypothesis that these numbers are the same against the alternative that the latter is greater than the former with p = 0.10 ($t = -1.30$). Compared to round 1, there is a statistically significant reduction in this number for both groups 1 ($p = 0.006, t = 3.67$) and 2 ($p = 0.001, t = 3.42$). When sets were selected by graduate students or contained undominated lotteries, about the same proportion participants chose them in groups 1 and 2 ($p = 0.34, t = 0.41$ for student selection and $p = 0.41, t = 0.23$ for undominated selection). There is also no significant change relative to rounds 5 and 6, in which no feedback was given with confidence level of 0.24.

Therefore, the only significant change observed when given feedback relative to when no feedback was given is a reduction in the proportion of small sets chosen under random selection. This suggests that participants expected to receive negative feedback when choosing the randomly selected set, and avoided this by choosing the large set. Moreover, this negative feedback reduced utility from the random sets and affected decisions, possibly due to anticipated regret. On the other hand, the data suggests that expected feedback from choice of the small sets in the other two selection mechanisms was positive or neutral, and thus did not significantly affect their decisions.

	5 x 25	**5 x 50**	**T-test**
Random	0.13	0.22	-1.30**
Student	0.75	0.72	0.41
Undominated	0.77	0.76	0.23

**P-value=0.10

Table 6: Proportion of small sets chosen in rounds 4 - 6 in Group 1 (5x25) and Group 2 (5x50). Participants received feedback after their choices

Table 7 shows the proportion of participants who chose a small set in one of the three rounds conditional on choosing a small set in another of the three rounds. The numbers are similar to the unconditional proportions shown in table 6, and differ from 4 mainly as a result of the difference in the choice of randomly selected small sets previously described. The classification by types in table 8 shows, as expected, that the proportion of participants classified as value-of-information types increased relative to the no-feedback rounds, while those classified as cognitive overload types decreased. The proportion of participants classified as more is better types also increased slightly relative to the no-feedback rounds.

	5x25	**5x50**
P(undom|random)	0.71 (7)	0.75 (12)
P(student|random)	0.86 (7)	0.58 (12)
P(random|student)	0.14 (42)	0.18 (39)
P(undom|student)	0.83 (42)	0.82 (39)
P(student|undom)	0.81 (43)	0.78 (41)
P(random|undom)	0.12 (43)	0.22 (41)

*In parenthesis is number of observations

Table 7: Proportion of participants who chose one small set conditional on having chosen another. Participants received feedback - rounds 4 - 6.

	5 x 25	**5 x 50**
Cognitive Overload	0.07	0.13
Value-of-information	0.55	0.46
More is Better	0.23	0.18
Sum All	0.85	0.77

Table 8: Classification by types: Rounds 4 - 6

4.1.3 Experience: Rounds 7 - 24

Table 9 shows the proportion of small sets chosen in rounds 7 - 24. When selection was random, between 14% and 20% of participants in Group 1 and between 28% and 39% of participants in Group 2 chose the small set, with an average of 18% for Group 1 and 31% for Group 2. A two-sample Wilcoxon-Mann-Whitney rank-sum test for equality of the distributions in Groups 1 and 2 rejects the null hypothesis with p = 0.0035 ($z = -2.923$). As in the previous rounds, this is consistent with an increase in cognitive overload as the choice set increases. Note that, as expected, the numbers increased significantly relative to the rounds in which feedback was given.

Cuzick's (1985) test to investigate the presence of a trend in the choice of randomly selected sets cannot reject the null hypothesis of no trend with p = 0.63 ($z = 0.48$) for Group 1. For Group 2, however, the null hypothesis is rejected in favor of a positive trend at 0.05 significance level

($z = 1.7$). This suggests that experience with the large set made participants aware of the difficulty of the decision, inducing greater selection of the small set.

Table 9 also shows that between 73% and 79% of participants in Group 1 and 65% and 76% of participants in Group 2 chose the small set when the lotteries were selected by economics and Kellogg graduate students. A Wilcoxon-Mann-Whitney rank-sum test rejects the equality of the distribution at 0.01 level of significance ($z = 2.449$). This suggests that participants thought graduate students' choices would be better from the set of 25 lotteries than from the set of 50. This would be true, for example, if graduate students made more mistakes when choosing from the set of 50 lotteries than from the set of 25.

Cuzick's (1985) test cannot reject the null of no trend in choice of student selected sets with p = 0.23 ($z = 0.48$) in Group 1, but in Group 2 the null hypothesis is rejected in favor of a positive trend at 0.045 significance level ($z = 1.69$).

These results show that not only are value-of-information and cognitive overload important to explain why individuals prefer to have fewer options, but the effects do not go away when a decision is repeated, i.e., with experience. On the contrary, in the experiment experience generated an increase in the proportion of small sets chosen under random and student selection, possibly due to participants becoming aware of the difficulty in choosing from the large set.

The last two columns of Table 9 show that between 70% and 80% of participants in Group 1 and 76% and 80% in Group 2 chose the small sets when they contained the undominated lotteries. A two-sided Wilcoxon-Mann-Whitney rank-sum test rejects the equality of the distributions at 0.07 level of significance ($z = -1.783$). A one-sided test rejects the equality of the distribution against the alternative that the proportion of small-best sets chosen in Group 1 tend to be smaller than in Group 2 at 0.04 level of significance. Cuzick's (1985) test cannot reject the null of no trend for both groups with p = 0.15 ($z = -1.43$) for Group 1 and p = 1 for Group 2 ($z = 0$).

	Random		**Student**		**Undominated**	
	5x25	**5x50**	**5x25**	**5x50**	**5x25**	**5x50**
Rounds 7 - 9	0.14	0.28	0.73	0.65	0.80	0.78
Rounds 10 - 12	0.20	0.28	0.79	0.67	0.77	0.78
Rounds 13 - 15	0.20	0.28	0.79	0.70	0.70	0.76
Rounds 16 - 18	0.16	0.31	0.75	0.74	0.75	0.80
Rounds 19 - 21	0.20	0.39	0.79	0.76	0.75	0.80
Rounds 22 - 24	0.18	0.30	0.79	0.70	0.71	0.76

Table 9: Proportion of small sets chosen in rounds 7 - 24 in Group 1 (5x25) and Group 2 (5x50). No feedback was given.

Table 10 shows the conditional choice of small-sets averaged over rounds. The conditional results are similar to the marginal results and to the conditional results in the previous rounds.

	5x25	5x50
P(sm-best|sm-rand)	0.81 (60)	0.88 (99)
P(sm-stud|sm-rand)	0.79 (60)	0.88 (99)
P(sm-rand|sm-stud)	0.18 (259)	0.38 (228)
P(sm-best|sm-stud)	0.85 (259)	0.92 (228)
P(sm-stud|sm-best)	0.88 (251)	0.83 (252)
P(sm-rand|sm-best)	0.19 (251)	0.35 (252)
P(sm-rand & sm-stud & sm-best)	0.12 (336)	0.25 (324)

*In parenthesis is number of observations

Table 10: Average proportion of participants who chose one small set conditional on having chosen another. No feedback was given. Rounds 7 - 24.

The classification by types is shown in table 11. Each group of 3 rounds of different selection mechanisms is classified as before. This generates six different classifications by types, which are then averaged. For both groups, the value-of-information is most important in explaining why participants chose small sets. Cognitive overload is relatively small in Group 1, but becomes an important explanation in Group 2, when the large set has 50 lotteries. This classification accounts for 84% of behavior in Group 1 and 89% of behavior in Group 2. Thus, a relatively small number of participants are behaving in a way that cannot be explained in this setting.

	5 x 25	5 x 50
Cognitive Overload	0.12	0.25
Value-of-information	0.53	0.39
More is Better	0.19	0.25
Sum All	0.84	0.89

Table 11: Classification by types. Rounds 7 - 24

4.1.4 Pooled Data

I now discuss the aggregate data from all rounds of the experiment. Table 12 shows the number of times participants chose the small sets in groups 1 and 2. Recall that each group had eight rounds for each selection mechanism (random, students, undominated). The table shows the proportion of participants who chose the small sets N times, where $N = 0, ..., 8$ for each selection method. The table also shows the proportion of subjects who chose small sets N or more times, for $N = 3..., 7$.

Table 12 shows that the probability of choosing the small set $N+$ times when selection is random is consistently larger for Group 2 than for Group 1, with 26% of participants choosing the small-random sets five or more times out of eight. Thus, these participants showed a strong preference

N	Small-Random		Small-Students		Small-Best	
	5x25	**5x50**	**5x25**	**5x50**	**5x25**	**5x50**
0	0.46	0.31	0.11	0.06	0.09	0.07
1	0.30	0.22	0.05	0.07	0.04	0.00
2	0.07	0.09	0.02	0.06	0.04	0.04
3	0.02	0.06	0.04	0.07	0.04	0.04
4	0.00	0.06	0.04	0.02	0.07	0.07
5	0.00	0.04	0.02	0.09	0.02	0.13
6	0.05	0.09	0.05	0.09	0.05	0.02
7	0.02	0.04	0.09	0.13	0.14	0.11
8	0.07	0.09	0.59	0.41	0.52	0.52
3+	0.16	0.37	0.82	0.81	0.84	0.89
4+	0.14	0.31	0.79	0.74	0.80	0.85
5+	0.14	0.26	0.75	0.72	0.73	0.78
6+	0.14	0.22	0.73	0.63	0.71	0.65
7+	0.09	0.13	0.68	0.54	0.66	0.63

Table 12: Proportion of subjects who chose N and N or more small sets.

for the small randomly selected sets even after experimenting with the large sets. This is a very large number considering that they could have ignored extra lotteries from the large sets, and is consistent with the argument that individuals do not do that in practice, i.e., they have cognitive overload. This effect is not as strong in Group 1, which suggests that contemplation costs were not as large in this case because of the smaller number of alternatives. A one-sided Wilcoxon-Mann-Whitney rank-sum test of equality of distributions rejects the null hypothesis at 0.036 level of significance ($z = -1.798$).

The table also shows that participants in both groups seem to trust the ability of the graduate students in selecting lotteries, with over 70% of them choosing the student selected sets five or more times out of eight. This increase in the proportion of small sets chosen when compared to random selection supports value-of-information as an important explanation for why participants preferred fewer options. A Wilcoxon-Mann-Whitney rank-sum test cannot reject the null of equality of distributions of Group 1 and Group 2 with p = 0.25 ($z = 1.149$). Thus, participants seem to be equally trusting of the ability of graduate students choices in both groups.

The results for the choice of undominated sets are similar to the choice of student selected sets. Over 70% of participants chose the undominated sets five or more times out of eight, both in groups 1 and 2. In addition, one cannot reject the equality of the distributions using a Wilcoxon-Mann-Whitney rank-sum test with p = 0.91 ($z = -0.10$). This is consistent with some proportion of participants having zero or very low contemplation costs.

Table 13 classifies participants into types. A cognitive overload type each small set five of more times out of eight. A value-of-information type chose the randomly selected sets at most three times out of eight, and the student selected set and the undominated set five or more times out of eight. A more is better type chose the random and student sets at most three times each. These three types account for over 85% of behavior in the sample.

Around 65% of participants can be classified into one of the first two types, that is, with generally preferring to have fewer options, and slightly over 20% of participants' behavior is consistent with preference for more options. Of those who preferred less, value-of-information is found to be the most important reason in both groups. The effect of cognitive overload is not very important for Group 1. However, it accounts for 24% of the behavior in Group 2, outweighing the more is better types. As was previously argued, this suggests that as the set size increases, so do contemplation costs and thus the importance of cognitive overload as an explanation for why individuals prefer to have less choices. It is interesting to see that the proportion of more is better types is constant from Group 1 to Group 2, which generally occurs as well in the disaggregated analysis of the rounds.

	5 x 25	**5 x 50**
Cognitive Overload	0.11	0.24
Value-of-information	0.54	0.43
More is Better	0.21	0.22
Sum All	0.86	0.89

Table 13: Classification by types: Pooled data.

4.1.5 Further Analysis of Pooled Data

I estimate the expected number of times participants chose the small sets conditional on demographic variables and levels of risk aversion as elicited by the Holt and Laury (2002) procedure. The maximum number of times each small set could be chosen was 8, since there were a total of 24 rounds and there were three sampling methods. I include two dummy variables (dummy student and dummy undom) to account for the different sampling conditions. Table 14 presents the results.

The dummy coefficients on the selection process are positive and statistically significant at 5% for Group 1 but not for Group 2. For Group 1, the average number of times the small set is chosen under the student and best selection is around 4.6 and 4.8, respectively, larger than under random selection, conditional on the regressors. The level of risk-aversion is interacted with the dummy variables for the selection methods. The negative and statistically significant coefficient (at 5%) on risk-aversion means that higher levels of risk-aversion are associated with fewer choices of the small randomly selected sets. The coefficient is small in magnitude, however. When interacted with the dummies, risk-aversion is again statistically significant at 5% but now has a positive sign. Thus, more risk-averse participants chose on average more student or undominated selected sets than less risk-averse participants. Gender is statistically significant at 10% in Group 1 and at 5% in Group 2. In both cases, males chose the small sets fewer times on average than females (0.89 in Group 1 and 1.31 in Group 2) conditional on the other regressors. Field of study is generally not significant (except eng/math/stats in Group 2, at 10%). Participants with more background in economics on average chose fewer student selected sets in Group 2 (significant at 5%) and more undominated sets in Group 1 (significant at 10%).

Dep. variable: Number of times small set is chosen				
	Group 1 (5 x 25)		Group 2 (5 x 50)	
Indep. variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
constant	11.85	7.67	8.14*	2.75
dummy student	4.48*	1.98	-0.11	1.83
dummy best	4.17*	1.97	-0.65	1.72
age	-0.40	0.43	-0.01	0.14
risk-aversion	-0.12*	0.20	-0.67*	0.24
risk-aversion*dummy stud	-0.20	0.27	0.88*	0.33
risk-aversion*dummy undom	-0.34	0.27	1.12*	0.34
gender (d=0, female)	-0.89**	0.47	-1.31*	0.44
biology	-0.51	0.90	0.64	1.76
eng/math/stats	0.07	1.01	-2.56**	1.40
language/journ/soc science	0.66	0.77	-0.62	0.91
psychology	-0.89	1.71	-1.39	1.39
more than one field	-0.65	0.68	-0.51	0.82
class	0.37	0.43	0.20	0.25
stats background	-0.06	0.43	0.13	0.24
econ background	-0.74	0.64	-0.46	0.40
econ back*dummy stud	0.56	0.86	-2.22*	1.07
econ back*dummy undom	1.46**	0.86	-1.45	0.94
stats back*dummy stud	0.007	0.59	0.01	0.67
stats back*dummy undom	-0.33	0.59	-0.07	0.37

N = 168 for treatment 1; N = 162 for treatment 2
*Statistically significant at 5%
**Statistically significant at 10%

Table 14: Number of times small set is chosen conditional on independent variables

Table 15 shows the average time in seconds spent in choosing a lottery from the sets selected. It can be seen that participants who chose the small sets spent on average half of the time as participants who chose the large sets in rounds 1 - 6. From then on, because the large sets were the same, participants who chose the small sets were taking relatively more time to select a lottery. The decrease in time spent making each decision is probably due to learning and experience with the task. Because of the self-selection into the sets, however, one cannot claim there is a causal relation between observed contemplation costs and choice of sets.

Participants' decisions can be ranked by whether or not they chose a strictly dominated lottery from each set selected. Table 16 shows the proportion of participants who chose an undominated

Round	**Large**		**Small**	
	5x25	**5x50**	**5x25**	**5x50**
1 - Random	62.0	96.3	28	41.4
2 - Student	62.2	63.6	37.6	31.1
3 - Undom	46.6	72.8	43.8	31.7
4 - Random	73.4	77.3	14.5	34.5
5 - Student	48.5	38.7	39.8	29.4
6 - Undom	51.0	47.1	46.3	26.6
7 - Random	79.9	77.1	19.2	33.4
8 - Student	57.7	49.6	42.6	37.7
9 - Undom	55.2	29.8	36.1	27.2
10 - Student	39.3	26.0	29.0	29.0
11 - Random	41.6	31.0	34.2	32.7
12 - Undom	28.1	8.0	24.9	21.2
13 - Random	33.3	27.8	26.4	22.0
14 - Student	33.0	13.1	17.0	22.5
15 - Undom	19.1	8.1	19.0	16.2
16 - Student	17.2	6.3	17.1	18.0
17 - Random	23.3	15.1	27.1	18.8
18 - Undom	11.8	2.4	15.8	15.5
19 - Random	19.4	12.2	17.7	17.6
20 - Undom	8.1	3.5	11.5	13.0
21 - Student	10.6	6.7	12.0	13.7
22 - Undom	10.1	4.7	11.5	11.8
23 - Random	17.6	12.4	24.0	13.5
24 - Student	11.9	5.3	12.4	12.5

Table 15: Average time spent choosing a lottery per round (in seconds)

lottery. The number in parenthesis shows how many people chose each set. The proportion of participants who chose a lottery that is not dominated is much higher for sets of 25 lotteries when compared to large sets of 50 lotteries. The Wilcoxon rank-sum test rejects the null hypothesis that the samples come from the same distribution for all three conditions as well as for the pooled data with 0.01 significance level. Because of self-selection into sets, it is not possible to analyze how choice of sets was affected by the likelihood that a participant chose an undominated lottery. However, this can be studied by comparing choices with those from Treatment 2, in which there is no self-selection as participants were assigned the sets of lotteries, instead of choosing between them. I now discuss these issues.

Round	**Large**		**Small**	
	5x25	**5x50**	**5x25**	**5x50**
1 - Random	0.63 (38)	0.57 (28)	0.83 (18)	1.00 (26)
2 - Students	0.88 (16)	0.60 (15)	0.90 (40)	0.90 (39)
3 - Undom	0.91 (11)	0.57 (14)	1.00 (45)	1.00 (40)
4 - Random	0.90 (49)	0.64 (42)	0.71 (7)	1.00 (12)
5 - Students	0.79 (14)	0.80 (15)	0.90 (42)	0.90 (39)
6 - Undom	0.77 (13)	0.85 (13)	1.00 (43)	1.00 (41)
7 - Random	0.85 (48)	0.79 (39)	1.00 (8)	1.00 (15)
8 - Student	0.93 (15)	0.58 (19)	0.90 (41)	0.89 (35)
9 - Undom	0.91 (11)	0.58 (12)	1.00 (45)	1.00 (42)
10 - Student	1.00 (12)	0.61 (18)	0.93 (44)	0.92 (36)
11 - Random	0.84 (45)	0.67 (39)	1.00 (11)	0.93 (15)
12 - Undom	0.85 (13)	0.67 (12)	1.00 (43)	1.00 (42)
13 - Random	0.87 (45)	0.69 (39)	1.00 (11)	0.87 (15)
14 - Student	1.00 (12)	0.63 (16)	0.91 (44)	0.79 (38)
15 - Undom	0.94 (17)	0.62 (13)	1.00 (39)	1.00 (41)
16 - Student	0.93 (14)	0.60 (15)	0.90 (42)	0.80 (40)
17 - Random	0.91 (47)	0.62 (37)	1.00 (9)	0.71 (17)
18 - Undom	1.00 (14)	0.64 (11)	1.00 (42)	1.00 (43)
19 - Random	0.91 (45)	0.76 (33)	1.00 (11)	1.00 (21)
20 - Undom	1.00 (14)	0.73 (11)	1.00 (42)	1.00 (43)
21 - Students	0.83 (12)	0.62 (13)	0.95 (44)	0.78 (41)
22 - Undom	0.94 (16)	0.69 (13)	1.00 (40)	1.00 (41)
23 - Random	0.96 (46)	0.74 (38)	0.90 (10)	0.69 (16)
24 - Students	1.00 (12)	0.75 (16)	0.91 (44)	0.79 (38)

*The number of observations is in parenthesis.

Table 16: Proportion of participants who chose an undominated lottery

4.2 Treatment 2

In treatment 2, participants were given the sets of lotteries of treatment 1 and asked to choose one lottery from each of these sets. Thus, participants did not choose between sets in treatment

2. By comparing the choice of lotteries when sets are endogenous to when they are exogenous, it is possible to investigate whether subjects who chose the large sets the most in treatment 1 self-selected themselves into larger sets because of higher ability, or alternatively, whether they were too optimistic about their ability and actually made worse decisions on average relative to a person choosing from the large set in treatment 2.

I rank participants' decisions according to whether or not they chose a dominated lottery from each of the sets they faced. In treatment 1, they faced only the sets they selected. In treatment 2, participants received all the sets which a treatment 1 participant could potentially face.

Recall that there were two conditions in treatment 2, which varied according to the order in which sets were given to participants, with some receiving the small sets first, while others receiving the large sets first. This was done to control for possible learning effects. In the analysis that follows, I use the pooled data of conditions 1 and 2 since a Wilcoxon-Mann-Whitney rank-sum test of equality of the distributions of the two conditions cannot reject the null with p = 0.65 (z = -0.449). The results of the analysis are similar regardless of whether the pooled or disaggregated data is used.

To study how selection into large sets was related to ability, I compare the average proportion of undominated lotteries chosen by individuals who selected a large set in treatment 1 to the average proportion of undominated lotteries chosen by participants in treatment 2. If a participant in treatment 1 has relatively high ability, his average performance over all large sets chosen should be higher than the average performance of a participant in treatment 2. Then, I study whether higher ability participants in treatment 1 were more likely to choose a large set over a small one.

Let $p_{j,2}$ denote the average proportion of participants who chose an undominated lottery in large set $j = 1, ..., J$ in treatment 2. Let I_{ji1} denote an indicator function that equals 1 when individual i in treatment 1 chose an undominated lottery from large set j, and zero otherwise. Then, $I_{ji1} - p_{j,2}$ is participant i's performance in choosing from set j relative to the average in treatment 2 and $\sum_{j=1}^{J} (I_{ji1} - p_{j,2})$ is i's average performance relative to participants in treatment 2 over all sets. The larger this number, the better is participant i of treatment 1 relative to the average of treatment 2 in choosing lotteries from the large sets. Figure 7 shows this variable across participants and the number of large sets chosen by them in treatment 1, as well as the correlations.

The correlation between the number of times a large set is chosen and the average relative performance of individuals in treatment 1 is 0.32 for Group 1 and 0.18 for Group 2. Thus, participants with relatively better performance in choosing from large sets of lotteries were less likely to select a small set. However, participants who chose relatively more dominated lotteries from large sets preferred to restrict their choices more often by choosing small sets. This is evidence that participants self-selected themselves into large sets due to higher ability, although the effect decreases from Group 1 to Group 2. These results do not change significantly when one conditions on demographic variables.

Note that participants with relatively worse performance often chose small sets that were randomly selected, and thus were likely to have relatively worse lotteries. Therefore, they seemed to prefer not choosing a dominated lottery directly. One possible explanation is that participants were not willing to randomly select lotteries, and this generated cognitive overload. To avoid it, participants preferred to choose lotteries from smaller sets.

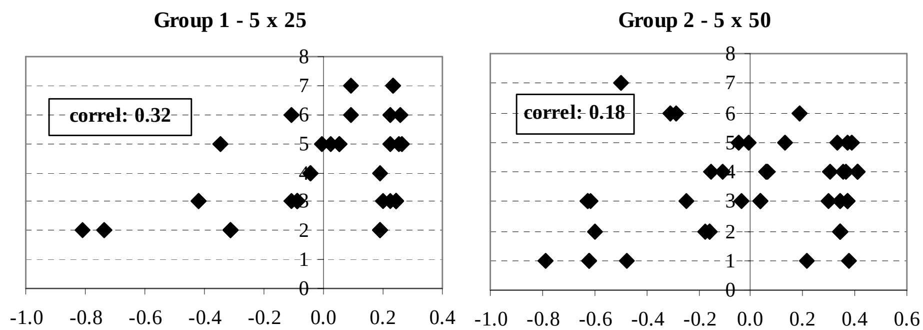

Figure 7: Number of large sets chosen vs average difference between probability of choosing undominated in treatment 1 and treatment 2.

5 Debriefing

I now show what some of the participants wrote in response to the following question in the last part of the experiment: "Please tell us about your strategy for choosing between GROUPS of lottery tickets. I would really appreciate a detailed response to this question."

5.1 Cognitive overload types wrote...

- "It's better to deal with a smaller group of numbers rather than a large group of numbers. Dealing with a larger number creates uncertainty and confusion. You are more likely to be comfortable dealing with a smaller group of numbers." (age: 21; gender: female; undergraduate; field: economics, senior)

- "I chose the small group of 5 tickets because it was easier to pick between 5 tickets than 25 tickets." (age: 22; gender: female; undergraduate; field: economics/engineering, senior)

- "I chose group A every time because I felt it would be easier to narrow it down from 5 choices than from 25 choices. Also, I chose group A when they were chosen by Kellogg students as the best possible choices." (age: 21; gender: male; undergraduate; field: other social science, junior)

- "I am terrible with any form of math, so I just chose the smaller groups because someone or something already made the decisions for me." (age: 19; gender: male; undergraduate; field: other, freshman)

- "I picked the smaller group because it allows me to determine exactly which of the 5 choices yields the highest return." (age: 22; gender: female; undergraduate; field: language, senior)
- "I didn't want to have to look at all of the tickets so I pretty much always chose option 1 to save time. I knew that one third of the time, this probably wasn't the best decision (when they were chosen at random), but for the sake of time it seemed worth it." (age: 21; gender: male; undergraduate; field: other social science, junior)
- "In deciding to choose between Group 1 and 2, it made more sense to go with Group 1 when they were prechosen by Kellogg and stats students. I felt more confident that these prechosen sets of five would be better options and I would have more of chance in winning. The first explanation didn't seem as impt. in choosing Group 1, so I chose Group 2 set of 50. However I felt it was overwhelming to choose from a set of 50 so in the next round after receiving feedback, I decided instead of picking a better number out of 50, to choose Group 1 since its easier to pick among 5 numbers than 50." (age: 29; gender: female; graduate; field: other social science)
- "i figured that i could better choose between the smaller groups becasue i wouldnt be so overwhelmed...and since i was choosing the best of each group..i eventually only picked the smaller group - the group of 50 was just too daunting."(age: 22; gender: female; undergraduate; field: language, freshman)

5.2 Value-of-information types wrote...

- "I don't know much about probabilities or lotteries, so I felt most confident when the small group was chosen by Kellogg students or determined "the best" by the experiment organizers. I figured I could select one randomly from the large group just as well as the computer could, so I chose group B when group A was chosen randomly." (age: 19; gender: female; undergraduate; field: language/journalism, sophomore)
- "When the option was random I never chose the smaller group, but in the other two cases I did taking into consideration that Kellogg students would have expertise and the other set would always give me the same or higher payments." (age: 21; gender: female; undergraduate; field: economics, senior)
- "If the smaller group was chosen randomly from the larger group, I chose the larger group because then none of the best lotteries would be eliminated. There was no point in choosing the smaller group in this case. However, if the smaller group was chosen from the larger group by knowledgeable students, or if the smaller group contained the best lottery tickets, I chose the smaller group. There was no reason to go through all 25 lotteries in the larger group if I knew the best were or most likely were in the smaller group of 5." (age: 19; gender: female; undergraduate; field: other social science, freshman)

- "Every time except once (and that once was just for fun), I chose the large group when the small group was to be randomly selected because I knew that I could at least randomly select as good as the computer could. Every time the small group would be chosen by the economics students to be the best I chose the small group because I thought the chances of them reducing the total list down to the best 5 were better than my chances. Every time the small group would be chosen to be the 5 best I chose the small group because I knew that my chances of determining the 5 best were not always going to be 100%." (age: 21; gender: male; undergraduate; field: other social science, junior)

- "I selected groups based on whether I thought the selection method would let me pick the best one. I did not want to lose the best ticket because of random selection. I trusted the Kellogg students and the"truth".to this question...as stated earlier I tried to maximize expected value of the ticket."

- "If the first group was random, I selected the second group because I knew group 1 might have eliminated the best lottery. For the group picked by Kellogg students, I figured they could choose better than I could. And for the 'best' group, I just trusted that those lotteries were best. Plus, I didn't enjoy thinking through all 50 or however many lotteries, so the smaller groups were easier to think through." (age: 19; gender: female; undergraduate; field: language/journalism, freshman)

- "For choosing GROUPS, I never chose the "random" option; I preferred to sort through the choices myself on the assumption that I am smarter than the random choices of the computer. I chose the "Kellogg student-approved" and "best options" option after verifying that the 5 choices offered there were also the 5 choices I had identified from the table as being good bets." (age: 21; gender: female; undergraduate; field: language, junior)

- "too many choices was bad. if the group was described as better in any way i perferred the small one not especially because it was chosen by grad students mostly because it was smaller and therefore easier to process." (age: 20; gender: female; undergraduate; field: biology, junior)

5.3 More is better types wrote...

- "I would always choose the one with the most options. Other people (such as the graduate students), might have different priorities from me, and I wanted a potential for higher payouts, not just a better chance of getting a decent amount of money."

- "Since the subset exists of all lotteries in the large set, I can pick from the large set on my own instead of having my choices limited by some other mechanism.".

- "I felt that my decision making ability in choosing the lotteries was better then anyone elses, so I prefered to just choose from the 50 as the smaller group was just a subset of the larger

50". (age: 21; gender: male; undergraduate; field: econ/engineering, junior)

- "I picked the bigger group so I could make my own decision". (age: 22; gender: male; undergraduate; field: engineering, senior)
- "1) choosing B was a no-brainer. why give control to randomness? 2) i understand the process in which the set in A was chosen, but i don't know enough about the kellogg/grad students' risk preferences and utility function of money. for me, i am relatively risk averse and want to come away with at least a certain amount (which came out to be in the range of 4 plus 7/8/9). i don't know if the grad students share this same attitude. 3) again, i don't know how the computer judges what is "better" or higher payout - the expected value of the payout, based on pure probabilities [=P(A)A +P(B)B]? or does the computer also take into account a utility function for money? if so, i still don't know what that function is, so it would be risky to go by what the computer CLAIMS to be better." (age: 20; gender: male; undergraduate; field: economics, junior)
- Almost of the times I chose the large group, I prefer to select my lottery than let the decision to a random machine (no many probabilities to get the best choices) or to the Kellogg students, which might have been to conservatives. A couple of times I chose "the best group of lotteries" option, because I knew I was going to have the higher prizes there. (age: 28; gender: male; graduate; field: language/journalism)
- "Generally, I only chose "Group one" when it was guaranteed to pay as well or higher than "Group two." I was confident in my ability to choose the best ticket on my own, if it was not done for me." (age: 20; gender: male; undergraduate; field: language/journalism; sophomore)

5.4 Procedures

I now show what some of the participants wrote in response to the following question in the last part of the experiment: Please tell us about your strategy for choosing between lottery tickets within a group. I would really appreciate a detailed response to this question."

- "I looked for the highest low numbers. Then judged between tickets that had low numbers of 7 or 8, based on probability and how much I wanted to risk the extra dollar, etc"
- "I was looking for the best percentage chance of a double digit win, as a way to be able to more quickly scan through the lotteries. I was looking for a .6 in a low double digit or a .5 or .4 percent chance at a higher double digit win"
- "I chose prizes higher than 10 that had a 0.4 probability or better"
- "Risk adverse decisions. Eliminated choices that the lowest output would be less than ~40% of the total amt."

- "I decided that I wanted at least $6 so I looked for choices that guarenteed a minimum of $6. After that if there were ones that guarenteed higher payments such as $7 or $8 I usually went with that one. If it was between one that was $7 and $17 versus $8 and $9 I chose the $7 and $17 because there was a possibility that I could get $17 and I was already above my minimum of $6. $6 was just an arbitrary choice."

- "I just tried to add up the expected value of each ticket and pick the highest. Any mistake I made any picking the subo-optimal expected value was due to mental math errors."

- "I took the sum of each ticket's payoffs times their probabilities. That gets you the 'expected return.' That's the average amount I would get from each ticket. That's why it took so long."

- "if there was at least a .4 chance of getting a large prize, i usually chose that. it was really an arbitrary choice, but it just seemed close enough to .5 to seem possible, and, of course, i would prefer a larger prize."

6 Conclusions

In this paper, I investigate in a laboratory experiment the reasons for why individuals may prefer to have fewer options. The aim is to identify whether behavior is consistent with value-of-information or cognitive overload. According to value-of-information, an individual will prefer to have fewer options if he believes a smaller set provides him with information about the ranking of the alternatives, thus allowing him to save the costs of contemplation. According to the cognitive overload argument, decision costs may be increasing in the size of the choice set because individuals necessarily contemplate more alternatives as their choice set expands. Thus, decision costs may increase more than the benefits as individuals face more options, and thus a smaller set may be preferred.

I conducted a laboratory experiment to investigate why individuals may prefer to have fewer options. Participants choose between small and large sets of lotteries in which the selection mechanism of the smaller set varied. Participants could not observe the small set. They observed only the large set and the information about how the lotteries in the small set were selected from the large set. After choosing the set, they would see it and choose one lottery from it. Small sets were selected from the large sets either randomly, by economics and Kellogg graduate students, or by including the only 5 undominated lotteries. Participants in Group 1 faced large sets with 25 lotteries, while participants in Group 2 faced large sets with 50 lotteries.

I found that 32% of participants in Group 1 and 48% of participants in Group 2 chose the small set under random selection, in support of cognitive overload. When selection was done by graduate students, around 70% of participants chose the small set in both groups 1 and 2. The numbers were similar when the small sets contained all five undominated lotteries.

The classification by types shows an increase in the relative importance of cognitive overload in Group 2 relative to Group 1. While 20% of participants choose the small sets in all three selection mechanisms (cognitive overload types) in Group 1, 33% did so in Group 2, showing that cognitive overload is important. In contrast, 43% of participants were classified as value-of-information types in Group 1, while 22% were classified as such in Group 2. This decrease in the proportion of participants classified as value-of-information types is consistent with increasing contemplation costs as the choice set increases in Group 1 to Group 2. I also shows that value-of-information is an important explanation for participants to prefer fewer options. The proportion of participants classified as more is better types was 19% in Group 1 and 15% in Group 2. Thus, the commonly used assumption in economics that people prefer to have more options is clearly violated in the data. In contrast, people seem to prefer fewer options largely due to value-of-information and cognitive overload. The relative importance of these two arguments seems to depend on the size of the choice sets.

When participants were given feedback about their choices of lotteries, the results changed in favor or value-of-information, as choice of the randomly selected sets decreased considerably. Thus, participants seemed aware that randomly selected sets would likely have worse lotteries and anticipated negative feedback when choosing these sets. Moreover, this negative feedback reduced utility from the random sets, affecting decisions.

When the large set was repeated to study the effect of experience and no feedback was given after choices, the proportion of randomly selected increased considerably relative to when feedback was given. In fact, there was a statistically significant positive trend in the choice of small randomly selected sets for Group 2, suggesting that experience with the large set made participants aware of the difficulty of the decision. A similar effect was found in the choice of sets selected by graduate students. Thus, I find that preference for fewer options does not go away, and even increases with experience with the decision.

In treatment 2, participants were given the sets of lotteries and asked to choose one lottery from each set. Thus, they did not choose between sets. I found that self selection into large sets in treatment 1 is related to higher ability. Participants who had below average performance in terms of choosing undominated lotteries from large sets did not choose them as often as those who had above average performance. In fact, they often chose small sets that were randomly selected, and thus were likely to have relatively worse lotteries. Therefore, they seemed to prefer not choosing a dominated lottery directly. One possible explanation is that participants were not willing to randomly select lotteries, and this generated cognitive overload. To avoid it, participants preferred to choose lotteries from smaller sets.

Thus, although a large part of economics is based on the assumption that individuals always want more choice, the data in this experiment shows that a relatively small percentage of individuals actually behaving consistently with this assumption. This is true even after participants have experience with the decision problem. I investigated possible reasons for this behavior and found that both, cognitive overload and value-of-information, are important in explaining the results.

These findings are important for firms' choices of product variety, as costs increase with the number of products offered. If consumers are better off with less variety, then firms can increase profits by reducing product lines. By understanding why individuals prefer to have fewer options, firms can design strategies in which they can reduce product variety while increasing sales. The findings in this paper suggest that simply reducing assortment may have these effects, as part of the consumers just seem to want fewer options. In addition, providing information about the selection in a way that is convincing to customers may attract more consumers, and thus should be a more profitable strategy.

The results in this paper can also help in the design of government policies, such as the Medicare Drug Discount Card Program, which has shown much lower than expected enrollment. Simple measures such as reducing the number of cards available or providing a list of recommended cards selected by a group of experts could increase enrollment and thus induce important improvements in welfare.

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8 Appendix A: Value-of-information

This section presents a model in which an individual has uncertainty about his preferences when choosing an alternative from a set. He can engage in costly contemplation to reduce this uncertainty, interpreted as the effort and time spent in making the decision. The individual chooses the amount of contemplation. If he chooses not to contemplate, these costs equal zero. The more he contemplates, the higher the cost, but the lower the uncertainty when selecting an alternative from the choice set. Therefore, first the amount of contemplation is chosen, and then one alternative is selected taking into account the information gathered and processed through contemplation. In this case, the individual may prefer a subset of a larger set, depending on his beliefs regarding how these options were selected. A smaller set may be preferred when it is believed to provide information about the ranking of the alternatives that otherwise would have to be acquired through costly contemplation.

Denote by X the finite set of all possible alternatives ever encountered by an individual and $P(X)$ the set of all nonempty subsets of X, i.e., all menus an individual can face. Let $\succcurlyeq$ be a binary preference relation on X, and the state-space S the possible preference orderings of the elements in X. Denote by μ the probability distribution over S, representing the individual's priors over the state-space. Thus μ represents the individual's priors regarding his preference ordering of the elements in X before any contemplation.

A set of partitions of S is given by $\Pi(S)$, with $\{S\} \subset \Pi(S)$. For any $s \in S$ and $\pi \in \Pi(S)$, $\pi(s)$ denotes the element of partition π that s belongs to. Thus, partition π reveals where in S the truth lies in. For $\pi, \rho \in \Pi(S)$, $\pi \geq_f \rho$ means that π is a weakly finer partition than ρ. A finer partition implies the decision maker has more information, since he knows the true state of the world lies in a smaller subset of S.

Let $A \subset X$ be the choice set faced by the decision maker. Before contemplating, the agent does not observe which elements are in A. This is equivalent to observing the elements but not knowing how A was generated. Instead, he imagines facing any of $A_j \in X$, $j = 1, ..., J$ sets of alternatives. His utility from A will depend on how likely he believes the different A_j 's are. For example, if the individual believes the set A was generated to be in line with his preferences, then he will assign high probabilities to A_j 's that give him high utility, and low probabilities to A_j 's that give him low utility. This will become more clear next, when I formalize individual beliefs about A_j and show how they affect the utility from A.

Let T denote the state-space of possible selections $A_j, j = 1, ..., J$ conditional on the state of the world s faced by the agent with choice set A. Let p_A be a probability distribution over T. Then p_A represents the probability distribution over selections, conditional on s. Therefore, p_A reveals the agent's confidence of how well A is aligned with his preferences if he contemplated fully. For example, the individual may believe that a set A will contain his most preferred alternative, whatever his tastes turn out to be. In this case, he will assign probability zero to receiving a set A_j that does not contain his most alternative for every possible state of the world s.

The agent maximizes expected utility, with state-dependent utility function $u : X \times S \to R$. He can reduce uncertainty using a costly contemplation strategy, represented by the choice of a partition $\pi \in \Pi(S)$, with $c : \Pi(S) \to R_+$ being the contemplation cost function. Let c be monotone in that $\pi \geq_f \rho$ implies $c(\pi) \geq c(\rho)$, i.e., reducing uncertainty is always weakly more costly. I assume for simplicity that $c(\pi_0) = 0$ (thus $c(\{S\}) = 0$), i.e., the cost of zero contemplation equals zero.

An individual who believes is facing $A_j \subseteq X$ and uses contemplation strategy $\pi \in \Pi(S)$ knows the true state of the world s lies in $E = \pi(s)$. Therefore, he restricts his maximization problem so that only states of the world in E are considered. For contemplation strategy π, the decision maker faces the following problem:

$$\max_{x \in A_j} \sum_{s \in E, s \in S} \mu(s|E) u(x, s) - c(\pi) \tag{1}$$

The contemplation strategy π is chosen by maximizing the ex-ante value of contemplation. The problem can be written as:

$$V(A_j) = \max_{\pi \in \Pi(S)} \left[\sum_{E \in \pi} \mu(E) \max_{x \in A_j} \sum_{s \in E, s \in S} \mu(s|E) u(x,s) - c(\pi) \right] \tag{2}$$

His utility from set A depends on his priors over A_j, conditional on A and on each state of the world s. Therefore, individual utility from set A is:

$$U(A) = \sum_{A_j \subseteq X} \sum_{s \in S} p_A(A_j|s) \mu(s) V(A_j) \tag{3}$$

From (3), it is possible to compare the utilities derived from all subsets $A \in P(X)$. The following lemma shows that if contemplation is costless, monotonicity will hold.

Lemma 1 *If $c(\cdot) = 0$, then $\forall\ B, C \in P(X)$ with $B \subset C, U(B) \leq U(C)$. Thus, an individual is always be better off with the larger set.*

Proof. From (1), it can be seen that if $c(\cdot) = 0$, an individual will fully contemplate to eliminate his uncertainty, because $\max(\cdot)$ is concave. Let $u_s^{C_k} = \max_{x \in C_k} u(x,s)$ and $u_s^{B_j} = \max_{x \in B_j} u(x,s)$, where $B_j \subseteq B$, $C_k \subseteq C$. For each k, let j_k be such that $B_{j_k} \subset C_k$, $\forall j_k$. Then by (3):

$$U(B) = \sum_{B_j \subseteq B} p_B(B_j|s) \mu(s) u_s^{B_j} = \tag{4}$$

$$= \sum_{C_k \subseteq C} p_C(C_k|s) \sum_{B_{j_k} \subseteq C_k} p_B(B_{j_k}|C_k, s) \mu(s) u_s^{B_{j_k}} \leq$$

$$\leq \sum_{C_k \subseteq C} p_C(C_k|s) \sum_{B_{j_k} \subseteq C_k} p_B(B_{j_k}|C_k, s) \mu(s) u_s^{C_k} =$$

$$= \sum_{C_k \subseteq C} p_C(C_k|s) u_s^{C_k} = U(C)$$

That is, $U(B) \leq U(C)$. ■

I now show that if contemplation is costly, there exists beliefs about the composition of the choice sets such an agent will have higher utility with fewer rather than more options.

Proposition 2 *Assume $c(\cdot) > 0$ and $B, C \subset X$ with $B \subset C$. There exists beliefs $p_C(\cdot|s)$ and $p_B(\cdot|s)$ such that $U(C) < U(B)$. Thus, the smaller set makes the individual better off.*

Proof. Let $B_j \subset B$, $C_k \subset C. \forall j, k$ and

$$u_s^X = \max_{x \in X} u(x,s) \text{ and } x_s^X = \arg\max_{x \in X} u(x,s) \tag{5}$$

Assume the following beliefs $p_B(\cdot|s)$:

$$p_B(B_j|s) = \begin{cases} 1, \text{ if } B_j = \{x_s^X\} \\ 0, \text{ otherwise} \end{cases}, \forall j \tag{6}$$

By (3) I have that:

$$U(B) = \sum_{s \in S} \mu(s) u_s^X = \tag{7}$$

$$= \sum_{s \in S} \sum_{C_k \subset C} p_C(C_k|s)\mu(s)u_s^X \geq$$

$$\geq \sum_{s \in S} \sum_{C_k \subset C} p_C(C_k|s)\mu(s)V(C_k) = U(C)$$

■

In this case, the agent believes that the small set predicts his tastes perfectly, even though it contains only one alternative. Meanwhile, it reduces the amount of contemplation needed to solve the decision to zero. Therefore, ex-ante, this set provides the individual with higher utility than any other set. Because the individual believes that the small set has one alternative that will give him the highest utility for every realization of the state of the world, the set is viewed as providing information about the ranking of the alternatives, and reduces the need of the agent to contemplate them. This happens when one delegates a decision to someone we fully trust to save the costs of gathering and processing information.

I now show that if the agent believes a small set is randomly selected from a large set, the large set will give him higher utility.

Remark 3 *Let $c(\cdot) > 0$, B,with $B \subset C \subset X$. Let N_B and N_C be the number of alternatives is B and C respectively. Assume the agent knows the number of alternatives in B, and uses this information when forming beliefs about the composition of B. Let $B_j \subset B$, $C_k \subset C$, and $B_{j_k} \subset C_k, \forall j, k$. Assume:*

$$p_B(B_{j_k}|C_k, s) = \frac{1}{\left(\frac{N_C!}{N_B!(N_C - N_B)!}\right)}, \forall s \tag{8}$$

That is, the agent believes that the alternatives in B are a random selection of the alternatives in C, for every possible composition of B and C. Then $U(B) < U(C)$, i.e. the larger set provides higher utility.

Proof. By (3),

$$U(B) = \sum_{s \in S} \sum_{B_j \subseteq X} p_B(B_j|s)\mu(s)V(B_j) = \tag{9}$$

$$= \sum_{s \in S} \sum_{C_k \subseteq C} p_C(C_k|s) \sum_{B_{j_k} \subseteq C_k} p_B(B_{j_k}|C_k, s)\mu(s)V(B_{j_k}) =$$

$$= \sum_{s \in S} \sum_{C_k \subseteq C} p_C(C_k|s) \sum_{B_{j_k} \subseteq C_k} \frac{1}{\left(\frac{N_C!}{N_B!(N_C - N_B)!}\right)} \mu(s) V(B_{j_k}) <$$

$$< \sum_{s \in S} \sum_{C_k \subseteq C} p_C(C_k|s) \mu(s) \sum_{B_{j_k} \subseteq C_k} \frac{1}{\left(\frac{N_C!}{N_B!(N_C - N_B)!}\right)} V(C_k) =$$

$$= \sum_{s \in S} \sum_{C_k \subseteq C} p_C(C_k|s) \mu(s) V(C_k) = U(C)$$

where the last equality is true since $\sum_{B_{j_k} \subseteq C_k} \frac{1}{\left(\frac{N_C!}{N_B!(N_C - N_B)!}\right)} = 1$. ■

Therefore, a given set is always better than a subset whose alternatives are believed to be randomly selected from it. This happens because the smaller set reduces the options to the individual without providing him with any information. In the model, this means that the individual believes the small set is generated independently of the state of the world, i.e., of his preference ordering. In fact, the individual can replicate a randomly selected smaller set himself by randomly ignoring alternatives from the larger set. Because taking them into account may be beneficial, he will be weakly better off with the larger set. Thus, it is because the individual believes that sets may be generated in a way that depends on the state of the world that it is possible to have preference for fewer options.

Note the importance of the uncertainty regarding the composition of the set. When there is no such uncertainty, Ergin (2003) proves a representation theorem for preferences in which the utility function derived incorporates contemplation costs that can be used to reduce uncertainty. His key axiom is monotonicity; that is, more options are weakly preferred by the agent. Because individuals can ignore extra alternatives as their choice set increases in size. When this is true, individuals contemplate only when doing so increases benefits more than costs.

9 Appendix B: Instructions

Note: I show the instructions for treatment 1. The instructions for the other treatments are similar and are available upon request.

Thank you for agreeing to participate in this experiment on individual decision making! Please do not talk to anyone during the experiment, or look at what anyone else is doing. You may ask questions at any time. The experiment will begin once you click "Continue".

I are interested in learning your tastes for "lottery tickets" and groups of lottery tickets. A lottery ticket gives probabilities with which you will get different amounts of cash. An example of a lottery ticket is to receive \$15 with probability 0.6 and \$9 with probability 0.4. Groups of lottery tickets will be organized in tables. The rows will show different lottery tickets. The columns will contain the monetary prizes and the probabilities associated with each of these prizes. Table 1 gives an example of a group of two lottery tickets. Lottery 1 gives \$10 with probability 0.5 and \$8 with probability 0.5. Lottery 2 gives \$20 with probability 0.2 and \$1 with probability 0.8.

Table 17: Table 1 - Example

lottery	**prize**	**probability**	**prize**	**probability**
1	10	0.5	8	0.5
2	20	0.2	1	0.8

Click "Continue" to go to the next slide.

The experiment will consist of 2 stages in which you will make several decisions involving lottery tickets. These will pay between \$3 and \$17. At the end of the experiment, one of the lottery tickets that you choose will be selected to determine your earnings. This will be done as follows: with probability 0.9, the lottery will be selected at random from your choices in Stage 1. With probability 0.1, the lottery will be selected at random from your choices in Stage 2. Therefore, your prize is much more likely to depend on your decisions in Stage 1 than in Stage 2. The result of this lottery ticket will be added to a \$4 participation fee. Therefore, you will earn between \$7 and \$21. Click "Continue" to go to the next slide.

Your choice of lotteries will determine your earnings, so you should make your decisions carefully. Even though you will make many choices, only ONE of them will determine your cash prize. Therefore, you should make all your decisions independently of each other. As soon as you are finished, you may leave. You will now go to Stage 1. You will receive instructions only for the stage that you are in. Click "Continue" to go to the next slide.

Stage 1

First, you will be asked to choose between two groups of lottery tickets, a large group and a small group. Then, you will get to pick one lottery ticket from each group that you choose. This will be done in 3 rounds. In each round, there will be a large group with 25 lottery tickets, and a small group with 5 lotteries selected from the large group. You will not be able to see the lotteries in the small groups, but you will be told how they were selected from the large group, which you will be able to see. Groups of lotteries will be different in each of the 3 rounds. Therefore, the 3 rounds are completely independent of each other. You will now go through a practice round. This will NOT count towards your cash prize. Click "Continue" to go to the next slide.

This is a practice round and will not count towards your cash prize. Please choose one of the following groups of lottery tickets (check either (a) or (b)):

(a)

Group of 5 lottery tickets described below

Here you will receive information about how the group of 5 lottery tickets was selected from the group of 25 shown in (b).

(b)

lottery	prize	probability	prize	probability
1	9	0.6	3	0.4
2	8	0.2	4	0.8
3	5	0.5	7	0.5
4	12	0.4	3	0.6
5	3	0.8	14	0.2
6	7	0.5	7	0.5
7	6	0.4	11	0.6
8	10	0.1	5	0.9
9	9	0.5	3	0.5
10	6	0.7	8	0.3
11	6	0.8	11	0.2
12	14	0.4	5	0.6
13	7	0.5	9	0.5
14	12	0.5	3	0.5
15	10	0.3	5	0.7
16	7	0.5	10	0.5
17	7	0.3	4	0.7
18	5	0.8	8	0.2
19	15	0.2	3	0.8
20	11	0.6	4	0.4
21	4	0.8	11	0.2
22	10	0.3	7	0.7
23	12	0.2	3	0.8
24	4	0.5	7	0.5
25	8	0.4	6	0.6

Figure 8: Instructions: Example.

Click "Continue" to go to the next slide.

[If participant clicks (a), he receives the following slide:]

Here's the group of lottery tickets you selected. Please choose one lottery from this group.

Group of 5 lottery tickets

lottery	prize	probability	prize	probability
1	12	0.5	3	0.5
2	4	0.8	11	0.2
3	9	0.5	3	0.5
4	5	0.5	7	0.5
5	15	0.2	3	0.8

Figure 9: Introduction: Example continued. Slide received if the small set is chosen.

Type the lottery number here:

[If participant clicks (b), he receives the following slide:]

Here's the group of lottery tickets you selected. Please choose one lottery from this group.

lottery	prize	probability	prize	probability
1	9	0.6	3	0.4
2	8	0.2	4	0.8
3	5	0.5	7	0.5
4	12	0.4	3	0.6
5	3	0.8	14	0.2
6	7	0.5	7	0.5
7	6	0.4	11	0.6
8	10	0.1	5	0.9
9	9	0.5	3	0.5
10	6	0.7	8	0.3
11	6	0.8	11	0.2
12	14	0.4	5	0.6
13	7	0.5	9	0.5
14	12	0.5	3	0.5
15	10	0.3	5	0.7
16	7	0.5	10	0.5
17	7	0.3	4	0.7
18	5	0.8	8	0.2
19	15	0.2	3	0.8
20	11	0.6	4	0.4
21	4	0.8	11	0.2
22	10	0.3	7	0.7
23	12	0.2	3	0.8
24	4	0.5	7	0.5
25	8	0.4	6	0.6

Figure 10: Introduction: Example continued. Slide received if the large set is chosen.

Type the lottery number here:

Now you are ready to make your decisions. For each of the following 3 rounds, first choose between the large group and the small group of lottery tickets. Then, choose one lottery ticket from the group you selected. Groups are different in each round. They are also different from the groups in the previous example. Recall that one of the lottery tickets that you choose throughout the entire experiment will be selected to determine your cash prize. This is what you will earn, in addition to the $4 participation fee. Click "Continue" to go to the next slide.

Please choose one of the following groups of lottery tickets (check either (a) or (b)):

(a)

Group of 5 lottery tickets described below

This group of 5 lottery tickets was randomly selected from the group of 25 shown in **(b)**. This was done by having a computer program randomly select 5 numbers from 1 to 25, corresponding to the 5 lotteries. If you want more details about how this was done, or what computer program was used, please ask the experimenter.

(b)

lottery	prize	probability	prize	probability
1	5	0.7	16	0.3
2	11	0.3	3	0.7
3	13	0.4	3	0.6
4	4	0.8	12	0.2
5	16	0.2	4	0.8
6	9	0.4	8	0.6
7	11	0.4	3	0.6
8	14	0.1	4	0.9
9	5	0.6	9	0.4
10	10	0.5	3	0.5
11	12	0.2	4	0.8
12	9	0.3	5	0.7
13	4	0.6	16	0.4
14	13	0.5	4	0.5
15	6	0.7	12	0.3
16	3	0.5	11	0.5
17	6	0.9	10	0.1
18	10	0.6	4	0.4
19	12	0.5	4	0.5
20	6	0.4	12	0.6
21	8	0.5	8	0.5
22	6	0.7	9	0.3
23	11	0.6	5	0.4
24	5	0.6	11	0.4
25	4	0.7	16	0.3

Figure 11: Instructions: Round 1.

Click "Continue" to go to the next slide.

[If participant clicks (a), he is shown the small set. If he clicks (b), he is shown the large set. This is ommitted here to save space. Full intructions can be requestion to the author.]

Please choose one of the following groups of lottery tickets (check either (a) or (b)): [See figure 12]

Click "Continue" to go to the next slide.

[If participant clicks (a), he is shown the small set. If he clicks (b), he is shown the large set. Available upon request]

Please choose one of the following groups of lottery tickets (check either (a) or (b)): [See figure 13]

Click "Continue" to go to the next slide.

[If participant clicks (a), he is shown the small set. If he clicks (b), he is shown the large set. Available upon request]

(a)

(b)

Group of 5 lottery tickets described below

This group of 5 lotteries was selected from the group of 50 in (b) by 10 economics and Kellogg graduate students. These students have extensive training in statistics, and solve these kinds of problems all the time. Here are some details: 10 students were given the set of 50 lotteries in (b) and asked to choose the 5 within the group which they thought were the best. This group contains 5 of the lotteries most frequently chosen by these 10 econ and Kellogg graduate students. If you need more details on this procedure or if you want to know more about who are the graduate students involved, please ask the experimenter.

lottery	prize	probability	prize	probability
1	3	0.6	10	0.4
2	5	0.8	13	0.2
3	15	0.4	4	0.6
4	6	0.6	10	0.4
5	17	0.1	4	0.9
6	11	0.5	6	0.5
7	5	0.7	13	0.3
8	5	0.9	17	0.1
9	9	0.5	7	0.5
10	12	0.4	3	0.6
11	14	0.2	3	0.8
12	3	0.5	11	0.5
13	3	0.8	16	0.2
14	14	0.3	3	0.7
15	6	0.6	14	0.4
16	12	0.6	3	0.4
17	6	0.3	8	0.7
18	12	0.4	3	0.6
19	3	0.7	14	0.3
20	8	0.5	10	0.5
21	10	0.4	6	0.6
22	6	0.7	11	0.3
23	13	0.4	5	0.6
24	9	0.5	5	0.5
25	17	0.2	5	0.8

Figure 12: Instructions: Round 2.

(a)

(b)

Group of 5 lottery tickets described below

This group of 5 lottery tickets was selected by taking the 5 best lotteries in the group of 50 shown in (b). This means that the lotteries in the small group will give you at least the same amount of money as the lotteries in the large group, and possibly more. Alternatively, for each lottery in the large group, there is a lottery in the small group that will give you at least the same amount of money, and possibly more.

lottery	prize	probability	prize	probability
1	12	0.2	4	0.8
2	4	0.6	10	0.4
3	8	0.5	5	0.5
4	10	0.3	4	0.7
5	3	0.8	15	0.2
6	5	0.4	9	0.6
7	11	0.5	4	0.5
8	4	0.4	13	0.6
9	10	0.5	5	0.5
10	10	0.6	4	0.4
11	5	0.7	8	0.3
12	4	0.6	16	0.4
13	5	0.2	10	0.8
14	12	0.3	4	0.7
15	17	0.2	6	0.8
16	4	0.5	12	0.5
17	8	0.9	7	0.1
18	3	0.5	13	0.5
19	11	0.3	4	0.7
20	3	0.7	16	0.3
21	4	0.6	11	0.4
22	4	0.5	10	0.5
23	14	0.4	4	0.6
24	15	0.3	3	0.7
25	4	0.5	8	0.5

Figure 13: Instructions: Round 3.

You will now be asked to make decisions in which you receive feedback regarding your choices of lottery tickets. That is, for each choice, you will be told whether or not there was a lottery ticket in the group that was better than the one you picked. You will get this information after you have made all your choices, but you will not be allowed to change them. You will do this in 3 rounds. Here's an example:

Assume your choices of lotteries in the 3 rounds were: (1) Lottery #1; (2) Lottery #3; (3) Lottery #5. An example of feedback you could receive is:

1. You could have chosen a lottery that gave you a higher cash prize for sure. Therefore, this was a bad choice.

2. There was no way you could have chosen a lottery that gave you a higher cash prize for sure. Therefore, you made a good choice. Congratulations!

3. You could have chosen a lottery that gave you a higher cash prize for sure. Therefore, this was a bad choice.

The feedback will be displayed on your screen after all choices have been made. Click "Continue" to go to the next slide.

For each of the following 3 rounds, please choose between the large group and the small group of lottery tickets (check either (a) or (b)). Remember that in each round, the small group is a subset of the large group. You will be told how the lottery tickets in the small group were selected from the large group. Groups are different in each round. Recall that one of the lottery tickets that you choose throughout the entire experiment will be selected to determine your cash prize. This is what you will earn, in addition to the $4 participation fee. At the end of the 3 rounds, you will receive feedback that will tell you how well you did in your choices of lottery tickets, when compared to other lotteries from the group. Click "Continue" to go to the next slide.

Please choose one of the following groups of lottery tickets (check either (a) or (b)):

[Similar to rounds 1-3. Ommitted to save space but available upon request]

Click "Continue" to go to the next slide.

Please choose one of the following groups of lottery tickets (check either (a) or (b)):

[Similar to rounds 1-3. Ommitted to save space but available upon request]

Click "Continue" to go to the next slide.

Please choose one of the following groups of lottery tickets (check either (a) or (b)):

[Similar to rounds 1-3. Ommitted to save space but available upon request]

Click "Continue" to go to the next slide.

Here's feedback in how you did in choosing the lottery tickets

1. [Feedback is given here]

2. [Feedback is given here]

3. [Feedback is given here]

Click "Continue" to go to the next slide.

Now, you will again be asked to choose between two groups of lottery tickets. Then, you will get to pick one lottery ticket from each group that you choose. As before, the large group will have 25 lottery tickets, and the small group will have 5 lotteries selected from the large group. You will not be able to see the lotteries in the small groups, but you will be told how they were selected from the large group, which you will be able to see. You will NOT receive any feedback after you have made your choices. All groups of lotteries are different than the ones you were faced with in Stage 1.

[Sequence of rounds similar to 1-3. Ommitted to save space but available upon request]

You have now finished Stage 1 and will begin Stage 2. In this stage, you will be asked to choose between two lottery tickets in several rounds. As before, the lottery tickets will be displayed in tables. For each round, please indicate which lottery ticket you prefer (type the lottery number in the space provided). You will be allowed to go back and forth between rounds and make changes to your answers if you desire to do so. Click "Continue" to go to the next slide.

Please choose one lottery ticket from the following group. Type the lottery number in the space provided.

[Holt and Laury procedure was described in section 3. Ommitted to save space but available upon request]

Click "Continue" to go to the next slide.

You are now finished with the two stages. Before making payments, I will ask you to answer a few questions about your experience during the experiment, as well as some demographic questions. Click "Continue" to go to the next slide.

1. Referring back to Stage 1, think about the decisions in which you DID NOT receive feedback. On average, what do you think is the percent chance that you chose the lottery ticket that was best for you in the group (the answer must be a number from 0 to 100).

2. Again in Stage 1, think about the decisions in which you DID receive feedback. On average, what do you think is the percent chance that you chose the lottery ticket that was best for you in the group (the answer must be a number from 0 to 100)., how did that make you feel? (If you did not receive this kind of feedback, please explain here).

3. Please tell us about your strategy for choosing between GROUPS of lottery tickets. I would really appreciate a detailed response to this question.

4. Please tell us about your strategy for choosing between lottery tickets within a group. I would really appreciate a detailed response to this question.
5. What is your age?
6. Your gender is:
   (a) Female
   (b) Male
7. Which best describes your program at Northwestern?
   (a) Undergraduate
   (b) Graduate
8. Which best describes your current fields of study (you may check as many fields as you wish)?
   (a) Biology
   (b) Economics
   (c) Engineering
   (d) Language, literature or journalism
   (e) Math or statistics
   (f) Psychology
   (g) Other social sciences
   (h) Other tech fields
   (i) Other (please specify)
9. What class at Northwestern are you?
   (a) Freshman
   (b) Sophmore
   (c) Junior
   (d) Senior
   (e) I'm a graduate student
10. To give us information about your familiarity with statistics, please pick the most advanced course in statistics that you have ever taken:
    (a) I have never taken any courses in statistics.
    (b) High school level statistics.

(c) Undergraduate introductory level course in statistics such as 202, or AP statistics test in High School.

(d) Undergraduate intermediate or advanced course in statistics, such as 330, or econometrics, such as 281.

(e) Graduate course in statistics.

11. To give us information about your familiarity with economics, please pick the most advanced course in economics that you have ever taken:

    (a) I have never taken any courses in economics.

    (b) Undergraduate introductory level course in economics such as 201 or 202.

    (c) Undergraduate intermediate or advanced course in economics, such as 310 or 311.

    (d) Graduate course in economics.

Thanks for answering these questions. You are now finished with the experiment. Please call the experimenter, so that your total cash prize can be calculated.

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