Age Effects and Heuristics in Decision Making*

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Abstract

Using controlled experiments, we examine how individuals make choices when faced with multiple options. Choice tasks are designed to mimic the selection of health insurance, prescription drug, or retirement savings plans. In our experiment, available options can be objectively ranked allowing us to examine optimal decision making. First, the probability of a person selecting the optimal option declines as the number of options increases, with the decline being more pronounced for older subjects. Second, heuristics differ by age with older subjects relying more on suboptimal decision rules. In a heuristics validation experiment, older subjects make worse decisions than younger subjects.

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"Having the opportunity to choose is no blessing
if we feel we do not have the wherewithal to choose wisely."
— Barry Schwartz, *The Paradox of Choice*

1 Introduction

Under standard economic assumptions about behavior, a decision maker can never be worse off when provided with more alternatives. This rests on the formalism that the supremum of any function on some set X is never less than the supremum on some subset Y contained in X. However, behavioral research suggests that individuals may have difficulty dealing with many alternatives. Faced with a multitude of options, they often postpone making a decision and are likely to be unhappy with their choices. Little is known about the quality of choices in such settings. A number of important decisions in life such as selecting retirement savings or medical insurance plans do involve a profusion of choice. This may lead to the selection of seemingly suboptimal plans (Iyengar and Kamenica 2010, Choi et al. 2010, Kling et al. 2008).

Our objective is to understand how individuals make complex decisions and why they sometimes make bad ones. We examine the frequency of optimal decision making in a simple experiment where subjects face choice sets with varying numbers of multi-attribute options. We are interested in how decision making varies with the nature of the choice task and with subjects' demographics. Furthermore, we investigate whether the use of heuristics or rules of thumb changes with age. Given the recent introduction of the Medicare Part D drug coverage program, we are particularly interested in examining differences in decision making between younger and older subjects.

Many researchers have identified aversion to choice in a variety of settings. Iyengar and Lepper (2000) show that consumers encountering a large assortment of jams or chocolates are less likely to make a purchase or express satisfaction with their choice than consumers presented with a smaller assortment. Redelmeier and Shafir (1995) and Roswarski and Murray (2006) show that physicians offered a greater choice of drugs to prescribe are less likely to prescribe *any* drug, while Iyengar et al. (2004) and Agnew and Szykman (2005) show that enrollment in workplace retirement savings plans decreases with the number of choices provided.

The recent introduction of prescription drug coverage into Medicare provides another example. As the new Medicare benefit was rolled out, reports in the popular press suggested seniors were "overwhelmed" by the 40 or more options presented to them. In one survey, very few seniors found this profusion of choice helpful, while 73% thought it would make plan selection "difficult and confusing" (Kaiser Family Foundation 2006). Frank and Newhouse (2007) argue that the complexity of Medicare Part D plans has discouraged enrollment and likely resulted in suboptimal choices. In addition, Heiss et al. (2007) argue that most of the 4.6 million Medicare recipients without prescription drug coverage would benefit from enrolling.

Most previous research on decision making in these settings has focused on whether a decision was made and one's self-reported satisfaction with the decision. Our paper departs from previous research by objectively measuring the optimality of subjects' decisions and by estimating the rules individuals use when making a choice. By examining how optimal decision making varies with age, to the best of our knowledge, we are the first to combine an objective measure of choice accuracy with age effects. Several field experiments have attempted to estimate optimal choices from actuarial or survey methods (Heiss et al. 2007 and Winter et al. 2006). However, these approaches tend to be limited by their inability to define the full choice set or quantify the value of each alternative for specific consumers.

In a study similar to ours, Schram and Sonnemans (2008) explore the effect of complexity on choice. They simulate the choice of stylized health-care plans with costly information acquisition in which subjects are provided with their health profile which deteriorates over the 35 periods of the experiment. They find that as the number of plans increases from 4 to 10, the quality of decisions decreases while the likelihood a subject switches to a new plan increases. Schram and Sonnemans (2008) build on the work of Payne et al. (1993) who examine a number of complex multi-attribute experiments in a variety of settings. They too find performance decreases with complexity. Tanius et al. (2009) examine the effect of the size of the choice set on the quality of decision making. In their experiment, two groups of subjects aged 18–64 and 65–91 faced a single task with either 6 or 24 options, where each option represented a simplified Medicare Part D plan. They too find that the quality of decision making decreases as the size of the choice set increases. However, in their experiment the quality of an option is not an objective measure.

Our experiments provide subjects with a series of multi-attribute choice tasks where one option is always objectively optimal. In particular, the ranking of options does not depend on subjects' risk preferences and requires only that subjects prefer more money to less. The full choice set is clearly defined, as is the value of each option. While the optimal option is always unique, its identity is concealed from subjects by manipulating both the number of attributes of each option and the number of options. Unlike Payne et al. (1993), Schram and Sonnemans (2008), and Tanius et al. (2009) our experiment is context-free and provides for an objective ranking of options independent of subjects' preferences. Moreover, in contrast to Payne et al. (1993) we provide our subjects with financial incentives. Tanius et al. (2009) provide a financial incentive unrelated to the performance in the task.

Unlike most experiments in economics, our subject pool includes individuals ranging in age from 18 to over 80. While the effect of sex on decision making in economic experiments has received considerable attention (Croson and Gneezy 2009, Eckel and Grossman 2008, Cox and Deck 2006), the effect of age has been much less studied. One notable exception is Kovalchik et al. (2005) who find little difference between older and younger subjects in a variety of experiments. In contrast, we find significant differences and discuss this apparent disparity later in the paper.

In our experiments, subjects make optimal choices in 40% of all choice tasks, with older subjects making more decision errors than younger participants. Those who hold graduate degrees make fewer errors, while other levels of education do not have a significant effect. Optimal decision making does not vary with sex. We find that increasing the number of options decreases the frequency of optimal choice. This effect is much larger for older subjects indicating a second-order effect of age: older subjects experience a greater increase in errors than younger subjects as the number of options increases. Overall, we show that older subjects make significantly less efficient decisions than younger subjects.

We examine several possible explanations for the age effect. We show that it cannot be explained by different levels of educational attainment across age. A higher stakes experiment replicates our initial findings, suggesting that economic explanations, such as search costs or wealth effects, are not a likely cause of differences in optimal decision making across age. We then focus on behavioral explanations by estimating simple decision rules or heuristics subjects may be using.

Individuals often use suboptimal decision rules when selecting among 401(k) plans. Common strategies include allocating equally among all choices (Benartzi and Thaler 2002, Huberman and Jiang 2006) or selecting the safest, low-yielding money-market funds (Iyengar and Kamenica 2010). Given limits on the brain's ability to retain and process information (Miller 1956, Cowan 2001), the use of heuristics simplifies the decision. Heuristics employed by younger and older people often differ. For instance, older individuals examine less information and consider fewer options when making choices (Cole and Balasubramanian 1993, Johnson 1993, Zwahr et al. 1999). Korniotis and Kumar (2010) use data on actual investment decisions of some 80,000 households and find that older investors are more likely to use common investment rules of thumb and are less skillful at applying them successfully.

If older and younger individuals approach decisions differently, this could have important policy implications. Can young adults be expected to make optimal retirement planning choices when presented with a variety of 401(k) investment options? Can older individuals be expected to make good choices when selecting medical or prescription drug insurance plans? Both decisions have a significant economic impact, as total assets in 401(k) plans exceed $1.8 trillion (EBRI 2005) and one of every twenty dollars in the United States is spent on health care for those over 65 years of age (Liu et al. 2007).

The psychology literature identifies several common heuristics individuals use to choose among multi-attribute options. Focusing on the most prominent ones, we fit a combined model to our data and establish the weights subjects allocate to these different decision-making strategies. We find heuristics differ with age. Older subjects tend to discard information on the relative importance of attributes, selecting options with the largest *number* of attributes. This is akin to selecting a prescription drug plan based only on the number of drugs each plan covers, and not the likelihood that each drug will be needed. We design a new experiment as a validation of the heuristics estimates. We again find older individuals make fewer optimal decisions as a consequence of their use of heuristics. We show that older subjects are more easily manipulated through presentation and design of options, which results in them not only making fewer optimal decisions, but also making less efficient decisions.

The cognitive powers of the human brain are not constant through life as cognitive function and working memory decline with age.[1] Perhaps as a result, older individuals appear to face greater difficulties with decisions (Frank 2007, Hanoch and Rice 2006, Hibbard et al. 2001) and are more prone to decision errors (Finucane et al. 2002). However, today's seniors may differ from today's younger population for reasons unrelated to the cognitive effects of aging. Generations may have distinctive traits that imply that today's youth will not resemble their grandparents in several decades. Differences in education, environment, culture, and economic conditions may contribute to differences observed in a cross-sectional study. However, from the standpoint of improving decision-making among today's seniors, the distinction between cognitive and cohort effects is less germane.

2 Experimental Design and Procedures

The experiment consists of a series of computerized choice tasks. In every task there are a number of distinct states that could occur with a known probability. Subjects choose among a set of options where an option is defined as a collection of states. Each task is represented in a tabular form, a simple, common method for presenting alternatives that is often preferred by subjects (Agnew and Szykman 2005). Figure 1 shows a screen shot of a sample task. The set of states forms the rows of the table and is labeled "Cards" while options are represented

[1]See, for example, Mittenberg et al. (1989), MacPherson et al. (2002), and Zelinski and Burnight (1997). With age, individuals experience lower recall (Gilchrist et al. 2008), reduced ability to make connections (Mitchell et al. 2000), less task focus (Isella et al. 2008), and slower information processing (Cerella 1985).

		Options			
	Odds	A select	B select	C select	D select
Card 1	24	✓		✓	✓
Card 2	8		✓		
Card 3	21	✓	✓	✓	
Card 4	26			✓	✓
Card 5	12	✓	✓		✓
Card 6	9	✓	✓		

Figure 1: **Screen shot of a sample choice task**

by columns and labeled alphabetically. Checkmarks in the Options column indicate all the states included in that option. Finally, the column labeled "Odds" shows the probability of a particular state occurring, presented to subjects as the number of each card type in a deck of 100 cards.

After a subject chooses an option, one state is selected at random. This is accomplished by having subjects draw one card from 100 randomly shuffled cards displayed face down on the screen. Once a subject draws a card by clicking on it, the number on every card is revealed. If the subject's chosen option contains the selected state, the subject earns \$1 for that task, and \$0 otherwise.

In the example in Figure 1, a subject who selects Option A would earn \$1 if one of the twenty-four Card 1s, or one of the twenty-one Card 3s, or one of the twelve Card 5s, or one of the nine Card 6s were drawn. Option C is the optimal choice as its expected payment of 0.71, found by summing the probabilities of covered states, is greater than the expected payment of any other option (0.66, 0.50, and 0.62 for Options A, B, and D). Drawing only one state after the subject chooses an option removes considerations of risk from the problem, allowing

States		Distribution				4 options				13 options								
6	10	PDF 1		PDF 2		A	B	C	D	E	F	G	H	I	J	K	L	M
Card 1	Card 1	21	15	2	1	✓		✓	✓	✓	✓		✓		✓		✓	
	Card 7		6		1	✓		✓	✓	✓	✓		✓		✓		✓	
Card 2	Card 2	26	10	38	22	✓	✓						✓	✓				✓
	Card 8		16		16	✓	✓						✓	✓				✓
Card 3	Card 3	12		1			✓	✓	✓	✓		✓		✓	✓	✓		
Card 4	Card 4	24	7	31	12	✓	✓	✓			✓	✓		✓	✓	✓	✓	✓
	Card 9		17		19	✓	✓	✓			✓	✓		✓	✓	✓	✓	✓
Card 5	Card 5	8		26					✓			✓	✓	✓	✓	✓	✓	
Card 6	Card 6	9	4	2	1			✓	✓	✓	✓		✓			✓	✓	✓
	Card 10		5		1			✓	✓	✓	✓		✓			✓	✓	✓

The table shows the eight option, distribution, and state combinations. Subjects see options A, B, C, and D, in 4-option tasks and options A through M in 13-option tasks. The likelihood of cards being drawn is dictated by either probability distribution PDF1 or PDF2. The 10-state tasks are derived by splitting some of the states in the 6-state tasks. The probability of the original state is allocated among the new (sub)states derived from it, and each (sub)state inherits the checkmark (or absence of a checkmark).

Table 1: **Experimental treatments**

for straightforward comparisons across subjects.

Subjects are presented with eight choice tasks constituting a $2 \times 2 \times 2$ within-subject design. The first dimension is the number of options (four or thirteen), the second is the probability distribution over states (PDF1 or PDF2), and the third is the number of states (six or ten). The full design is shown in Table 1. The example in Figure 1 corresponds to the 4-option 6-state PDF1 task.

The number of options in a choice task was either four or thirteen, representing a more than threefold increase across choice tasks. The distribution denoted PDF1 places more equitable though not identical weights on states, whereas most of the probability mass of PDF2 was concentrated on a few states. As a consequence, options under PDF1 have a smaller variation in payoffs, while under PDF2 payoffs are more widely distributed. Decisions under PDF2 may be easier for individuals who elect to focus on high-probability states and discount lower probability events (Camerer and Kunreuther 1989). The two distributions differ as the choice set expands from four to thirteen options. Under PDF1, the optimal option does not change as new (suboptimal) options are added. Under PDF2, expansion of the choice set provides a clearly superior alternative as the optimal option changes from an expected payoff of 0.71 to 0.96. More options are not helpful under PDF1, by design, while PDF2 offers a significant chance for improvement.

The minimum number of states is set at six to ensure that thirteen sufficiently-varied options could exist without including trivial options that covered either none or all of the possible states. The 10-state choice sets are formed from 6-state ones by splitting some states into multiple (sub)states. The probability of the new (sub)states totals that of the original state. Any option containing the original state contains all new (sub)states while options not containing the original state contain no new (sub)states. Thus, changing the number of states does not change the underlying structure of the choice set.

The order in which subjects saw the eight tasks was randomized to control for order effects. Subjects learned the result of each task before proceeding to the next one. They were not informed of the state and option expansion relationships. The order of options and states within each choice task was randomized, but relabeled to maintain an alphabetical/numerical ordering. Subjects completed the eight tasks after reading computerized directions (see appendix) and completing a 2-option 3-state task that served to familiarize subjects with the interface.

A total of 127 subjects participated in the experiment. Subjects were recruited through Vanderbilt University's eLab, a demographically diverse online panel of over 80,000 individuals interested in participating in online studies. The panel is recruited via links from partner sites, online advertisements, referrals from other panelists, and links from online search results, among other sources. Subjects for this study were randomly selected for invitations, stratified by age and sex, with equal numbers of men and women targeted within each age category. Given the large number of available panelists, eLab employs a two step procedure for selecting subjects. First, about five to ten thousand panelists are randomly selected from

	All	18–40	41–60	>60
Age (average)	50.7	29.8	50.2	67.4
Age (sd)	15.8	5.6	5.7	4.6
Male	54%	57%	62%	44%
High school	9%	6%	9%	13%
Some college	46%	51%	49%	38%
College degree	26%	31%	32%	16%
Postgraduate	19%	11%	11%	33%
Subjects	127	35	47	45

Table 2: **Demographic characteristics of the subject pool**

the entire pool subject to several conditions designed to maximize retention of panelists. Second, a sufficient number of panelists from this sub-pool are selected based on expected response rates for each person, obtained using a continuously updated response model. Selected subjects are sent an invitation email and two follow up emails over the next two weeks. For our study, the response rate exceeded 70%.

The average age of subjects was 50.7 with a standard deviation of 15.8. We grouped subjects into three age categories used in the subsequent analysis: 18–40 years old (thirty-five subjects), 41–60 years old (forty-seven subjects), and over the age of 60 (forty-five subjects). Summary statistics for the entire sample and for each age group are reported in Table 2. Males constitute 54% of our sample. In terms of educational attainment, 12 subjects had only a high school degree, 58 had some college education but not a degree, 33 had a college degree, and 24 were graduate degree holders. Every level of educational attainment is represented in each of the three age groups. The experiment took an average of 21 minutes, of which 7 minutes was used on active decision making. Subjects received an average payment of $9.02, including a $3 participation payment. Subjects were paid either by an online funds transfer or a mailed check at the conclusion of the experiment.

		Optimal	Nearly Optimal	Observations
All		40%	65%	1016
Options	4	47%	72%	508
	13	35%	58%	508
States	6	42%	65%	508
	10	39%	65%	508
PDF	1	35%	73%	508
	2	47%	57%	508
Age	18–40	52%	72%	280
	41–60	40%	65%	376
	>60	32%	59%	360
Sex	Men	40%	65%	552
	Women	41%	65%	464

Table 3: **Frequency of optimal choice**

3 Results

3.1 Optimal Decision Making

We begin our analysis with some general descriptive statistics of overall subject performance (see Table 3). Since every subject makes eight decisions, there are a total of 1,016 observed decisions. The optimal choice (with the highest expected payoff) was selected in 40% of all tasks. We define an option as "nearly optimal" if its expected payoff is within 10% of the optimal option's payoff. Such options were selected in two thirds of all tasks.

Subjects made better choices more often in 4-option tasks than in 13-option tasks, selecting both optimal and nearly optimal options with significantly greater frequency (Wilcoxon sign-rank $p < 0.001$).[2] Subject performance for both measures is far better than would be expected if they were making choices randomly, suggesting that the deterioration in performance is not simply an artifact of the design. Increasing the number of states from six to ten results in no significant differences.[3] Comparing the two probability distributions, optimal

[2] For each subject, we compare the frequency of (nearly) optimal choice in the four 4-option tasks to the frequency of (nearly) optimal choice in the four 13-option tasks.

[3] While the addition of four more states does not affect the frequency of optimal choice, it may have an effect on the distribution of chosen options. For example, with 13-option tasks in particular, there appears to be relatively more weight on the worst eleven options. Given the relatively small sample size it is difficult to test properly for such distributional effects.

choices were made in 47% of tasks with the extreme distribution (PDF2) compared to 35% with the more uniform distribution (PDF1) (Wilcoxon sign-rank $p < 0.001$). The opposite relationship holds for nearly optimal choices, though this can be attributed to the design of tasks. In 13-option tasks, PDF2 offered one superior option with an expected payoff of 0.96. No other option was close, meaning that optimal and nearly optimal coincide. PDF1 offered multiple nearly optimal choices, making it easier to select one of them.

Overall, summary statistics suggest (perhaps not surprisingly) that subjects have a harder time picking a needle out of a larger haystack than a smaller one. They also reveal a key finding of this study—decision making deteriorates with age. An optimal choice was made in 32% of all tasks faced by subjects over the age of 60 compared to 52% for those under 40 years of age. Similar patterns exist for nearly optimal decisions, with 60% of older subjects and 72% of younger subjects making nearly optimal decisions. Differences in both measures between the youngest and oldest groups are statistically significant (Mann Whitney $p < 0.021$). There are no significant differences between the middle and oldest groups (Mann Whitney $p > 0.225$), while the young and the middle groups differ mildly only in optimal decisions (Mann Whitney $p = 0.071$). There are no differences between men and women of any age group under either measure.

We estimate a probit model to investigate how decision characteristics and subject demographics impact the selection of optimal options (see Table 4). The unit of observation is a decision made by a subject. To control for the fact that each subject makes eight decisions, we estimate robust standard errors clustered by subject. In the first specification, we examine the main effects of the design. We add demographic characteristics of subjects as well as decision time in the subsequent three specifications.

In all specifications, we find that increasing the number of options from four to thirteen decreases the likelihood of selecting the optimal option. Increasing the number of states from six to ten has a negative, but generally insignificant effect. This is most likely due to the relatively small increase in the number of states across treatments or the way in which the increase in states was implemented. However, the estimated coefficient on the distribution

	(1)	(2)	(3)	(4)
13 Option Dummy	−0.333***	−0.350***	−0.192**	−0.308***
	(0.074)	(0.076)	(0.091)	(0.099)
10 State Dummy	−0.084	−0.088	−0.089	−0.147*
	(0.071)	(0.074)	(0.074)	(0.078)
PDF2 Dummy	0.312***	0.324***	0.329***	0.376***
	(0.064)	(0.066)	(0.066)	(0.070)
Age (Years)		−0.014***	−0.010*	−0.010**
		(0.005)	(0.005)	(0.005)
Male		−0.133	−0.155	−0.071
		(0.143)	(0.141)	(0.135)
Graduate Degree		0.576***	0.621***	0.577***
		(0.167)	(0.164)	(0.156)
13 Option Dummy			−0.479***	−0.502***
× Age > 60 Dummy			(0.183)	(0.191)
Decision Time				0.006***
				(0.001)
Decision Time^2/1000				−0.004***
				(0.001)
Constant	−0.199**	0.491*	0.244	0.077
	(0.090)	(0.277)	(0.301)	(0.287)
N	1016	1016	1016	1016
Log PseudoL	−668.7	−645.7	−640.8	−623.6

Parameter estimates (std. error) with *, **, and *** denoting significance at 10%, 5%, and 1%. Robust standard errors, clustered by subject.

Table 4: **Probit estimates for likelihood of optimal choice**

of states (PDF2 Dummy) indicates that a reduction in the number of *likely* states improves performance. Subjects more often select the optimal option when facing a task with the extreme probability distribution of states (PDF2) than when facing the distribution that places more equal weights on each state. Recall that PDF2 has half of the states collectively accounting for only a 5% chance of getting paid.

Age has a negative and highly significant impact on the likelihood that an individual will select the optimal option. There is no significant difference between men and women in the ability to select the optimal option, while a graduate degree has a positive and significant impact.[4]

Motivated by the effect of age, we examine the interaction between options and age by adding a dummy variable for the oldest age group facing 13-option tasks. In specification (3), the coefficient for this variable is negative and highly significant. This indicates a second-order effect of age. Beyond generally worse performance across all choice tasks, older subjects are disproportionately affected by the addition of more options. We explored other interactions with the older age group. Adding a dummy variable for the older group facing 10-state tasks results in a coefficient which is not significant with little change in other variables. If instead we include a dummy variable for the oldest group facing the 13-option 10-state task, the estimated coefficient is large, negative, and highly significant (-0.509, $p = 0.005$), with few changes to other variables.

In the last specification, we add the amount of time, measured in seconds, that each subject took to complete the task and time-squared to control for possible nonlinear effects of time. The addition of decision time does not alter other coefficients, with the exception of the number of states, which is now significant at the 10% level. Subjects who take more time to complete a task tend to be more likely to select the optimal option. We cannot draw causal inferences from this observation. It could be either that spending more time may lead to better decisions or that better decision-makers may spend more time. In particular, having an individual spend more time on a task will not necessarily result in a better decision. The squared decision time term indicates there is a limit to the positive effect of time on optimal decision making.[5]

[4] We only present results with a postgraduate education dummy as inclusion of 'some college education' and 'college degree' dummies produce similar results with neither being significant. A Wald test for the equality of the two dummies indicates that they are jointly equal to zero ($p = 0.258$). A Wald test that all three education dummies are jointly equal to zero indicates the null hypothesis of joint equality is rejected ($p = 0.003$).

[5] Several other methods of incorporating time into the analysis also do not change the qualitative results. For example, our results do not change if we instead use instruction time or total experiment time, or omit subjects who take the most and least amount of time or subjects who spend less than the median amount of time.

	All	Age			Sex	
		18–40	41–60	>60	Women	Men
Efficiency	86%	90%	87%	84%	87%	87%
Normalized Efficiency	47%	60%	44%	36%	47%	49%
Observations	1,016	280	376	360	552	464

Table 5: **Average efficiency by age**

3.2 Decision Making Efficiency

Our results indicate that the frequency of optimal decisions decreases both with the number of available options and with age. Next, we examine whether this translates to an overall decrease in the quality of decisions. One must be cautious in making comparisons across tasks for a given subject as the set of options differed, making errors more costly in some tasks than others. For example, selecting an option at random would lead to a greater loss relative to the optimal option under PDF2 than PDF1. Hence, our primary focus is on comparisons across subjects, for which cardinal measures of performance are valid.

Table 5 presents two measures of average quality of decisions. Efficiency represents the expected payoff of the chosen option divided by the expected payoff of the optimal option. Normalized efficiency is defined similarly except that the average expected payoff of all available options is subtracted from both the numerator and denominator. Thus, normalized efficiency represents improvement over selecting randomly, with 0% corresponding to random selection, and 100% corresponding to optimal choice. We calculate (normalized) efficiency of every decision and then average across all eight decisions each subject makes, arriving at a sample of 127 observations. Similar to our results on the frequency of optimal choice, older subjects make less efficient decisions. The mean efficiency of older subjects' decisions is 84% while that of younger subjects is 90%. This difference is highly statistically significant (Mann Whitney $p = 0.004$). According to our normalized efficiency measure, younger subjects select options much closer to the optimal one, with a 60% improvement over random choice. Older subjects experience a 36% improvement over random choice. The difference between these two groups is statistically significant (Mann Whitney $p = 0.007$). The difference between

	Efficiency	Normalized Efficiency	Optimality
Age	−0.182***	−0.696***	−0.525***
	(0.001)	(0.002)	(0.002)
Male	-1.503	−5.762	−4.957
	(0.019)	(0.073)	(0.051)
Graduate Degree	8.187***	31.389***	21.335***
	(0.025)	(0.095)	(0.067)
Constant	94.688***	79.633***	65.630***
	(0.034)	(0.131)	(0.093)
R^2	0.118	0.116	0.116

Parameter estimates (std. error) with *** denoting significance at 1%. Male is not significant at 10%. Dependent variable is the average of the measure across all choice tasks for each subject. $N = 127$.

Table 6: **OLS estimates of efficiency and demographics**

the young and middle aged groups is only marginally significant for both measures (Mann Whitney $p \approx 0.100$), while the difference between the middle and older aged groups is not significant.

In Table 6, we explore the role of demographic characteristics on decision making efficiency using ordinary least squares. The dependent variable is the average efficiency or average normalized efficiency across all eight decisions each subject makes, both measured on a scale of 0 to 100. The unit of observation is a subject, with a total of 127 observations. For comparison, we also present results with optimality as the dependent variable, where it is defined as the percentage of tasks in which a subject selected the optimal option. Again, age has a significant negative effect. Although the coefficient on the male dummy is negative, suggesting men do worse than women, it is not significant. A graduate degree makes a large difference increasing efficiency by about 8 percentage points and increasing improvement over random choice by about 31 percentage points. The effect of the graduate degree is equivalent to the estimated difference between a 20–year old and a 65–year old, holding all else equal.

	18–40	41–60	>60
High school	50%	31%	23%
Some college	48%	42%	35%
College	49%	28%	16%
Graduate degree	81%	70%	40%
Total	52%	40%	32%

Table 7: **Frequency of optimal choice by age and education**

4 Explaining the Age Effect

We examine several possible explanations for differences in behavior across age groups. The first one posits that the age effect is explained by differences in educational attainment across age groups. The other two explanations, one grounded in economic motives and another involving differences in problem-solving approaches, require we run additional experiments.

4.1 Age and Education

According to the U.S. Census, older individuals have lower educational attainment in the U.S. population.[6] Given the large role a graduate degree has in our results, the age effect could be explained by the educational attainment of each age group rather than age itself. Due to subject pool composition and response rates, our experiment oversampled higher educational attainment for older participants (see Table 2).[7] A full third of oldest subjects have a graduate degree. Thus, if educational attainment were to explain the age effect, our results should be quite the opposite of what we find. In addition, we find similar age effects within each education category, as well as a similar effect of educational attainment within each age group (see Table 7). While graduate degree holders perform better across all age groups, the younger graduate degree holders select the optimal option twice as often as older graduate degree holders.

[6]See data available at http://www.census.gov/population/www/socdemo/education/cps2008.html

[7]We did not stratify by education, but among the older population, individuals with higher levels of educational attainment are represented more in the subject pool and had higher response rates than individuals with lower educational attainment.

	Main Experiment			High Stakes		
	All	18-40	61+	All	18-40	61+
Age (average)	51.0	29.8	67.4	47.5	30.0	65.6
Age (std)	19.4	5.6	4.6	18.6	5.4	4.2
Male	50.0%	57.1%	44.4%	47.6%	50.0%	45.2%
High school	10.0%	5.7%	13.3%	17.5%	15.6%	19.4%
Some college	43.8%	51.4%	37.8%	57.1%	50.0%	64.5%
College degree	22.5%	31.4%	15.6%	14.3%	21.9%	6.5%
Postgraduate	23.8%	11.4%	33.3%	11.1%	12.5%	9.7%
Subjects	80	35	45	63	32	31

Table 8: **Demographic characteristics of the high stakes subject pool**

4.2 High Stakes

It is possible older subjects are wealthier on average and are less sensitive to incentives provided in our experiment. To investigate the role of wealth effects and evaluate if performance improves with remuneration, we conducted an additional experiment. We employed a fractional factorial design, selecting four of the eight original tasks with stakes ten times those used in the main experiment.[8] Subjects were paid \$10 per task if their selected option covered the realized state. Subjects also received a \$3 participation payment as in the original experiment. Selecting from the same set of tasks as our main experiment keeps the difficulty of the task constant while significantly increasing the cost of suboptimal decision making. Thus, explanations rooted in wealth effects would predict an improvement in decision making.

Subjects were stratified by age and sex. A total of 63 new subjects were recruited, with thirty two under the age of 40 and thirty one over the age of 60 with the intention of contrasting the oldest with the youngest subjects. Table 8 compares the demographic characteristics of the high stakes subject pool with that for the main experiment for which we include only subjects in the youngest and oldest age groups. Note that the two subject pools are very similar with the largest difference being the lower educational attainment of the high stakes pool. Subjects took an average of 13 minutes for the entire experiment and earned an average of \$28.50. Though the total time for the experiment was shorter than in the main experiment due to subjects facing four, instead of eight, tasks, higher stakes did

[8]The selected tasks were (listed as options, states, PDF): (4,6,1), (13,6,2), (13,10,1), and (4,10,2).

encourage subjects to invest more time in each decision. Subjects took an average of 59 seconds for making each decision, measured from the time it was presented until a choice was confirmed. This is 22% longer than in the main (lower stakes) experiment (Mann Whitney $p = 0.028$).

Despite spending more time on each decision, subjects facing a larger reward do not make better choices. Summary statistics for the high stakes experiment and the four corresponding tasks in the main experiment are presented in Table 9. Increasing stakes has no impact on the younger age group under any of the four performance measures (Mann Whitney $p > 0.504$ for each measure). For the older age group, performance actually declines with higher stakes, though significance varies by measure (Mann Whitney p-values between 0.028 and 0.089).

Pooling together low stakes and high stakes data for identical tasks, we re-estimate the likelihood of selecting the optimal option using probit. To capture differences between the size of stakes, we introduce a dummy variable for high stakes tasks (see Table 10). Age and graduate education again are highly significant. The magnitude of the age variable increases markedly from the low stakes experiment, in line with our summary statistics showing even greater differences in performance across age groups.[9] The inclusion of time in the regression does not affect estimates qualitatively, but more time spent on a task is associated with better performance. In all three specifications, the coefficient on the high stakes dummy is negative

[9]It is possible that demographic differences in educational attainment across our samples and experiments drive some of these results. To examine this, we also analyzed these differences within each educational category. We find that our main results hold. In particular, performance in the high stakes experiment is similar to performance in the main experiment for each age group and educational category. Also, within each education category, older subjects have a significantly lower frequency of optimal choice than younger subjects.

	High Stakes Experiment		Main Experiment (Corresponding Choice Tasks)	
	18–40	>60	18–40	>60
Optimality	57%	21%	56%	32%
Near Optimality	76%	44%	73%	59%
Relative Efficiency	90%	77%	90%	84%
Normalized Efficiency	62%	13%	61%	38%
Subjects	32	31	35	45

Table 9: **High stakes experiment summary statistics**

but not significant ($p > .232$ for all three specifications).[10] These results demonstrate that performance does not improve in the high stakes experiment.

[10]We also replicated our analysis of Table 4 and Table 6 using only high stakes data. We found patterns of significance identical to those in the main experiment. Additionally, since the high stakes experiment had four tasks while the main experiment had eight, it is possible that the main experiment allowed for more learning. We replicate the analysis in Table 10 using corresponding tasks from the main experiment only when they occurred in the first four tasks finding no change in our results.

	(1)	(2)	(3)
13 Option Dummy	−0.289***	−0.069	−0.169
	(0.105)	(0.140)	(0.146)
10 State Dummy	−0.150	−0.164*	−0.263**
	(0.094)	(0.097)	(0.107)
PDF2 Dummy	0.396***	0.406***	0.440***
	(0.095)	(0.095)	(0.100)
Age (Years)	−0.023***	−0.018***	−0.018***
	(0.004)	(0.005)	(0.005)
Male	−0.226	−0.231	−0.202
	(0.145)	(0.145)	(0.140)
Graduate Degree	0.529***	0.540***	0.523***
	(0.174)	(0.174)	(0.171)
13 Option Dummy		−0.449**	−0.458**
× Age > 60 Dummy		(0.216)	(0.223)
High Stakes Dummy	−0.116	−0.112	−0.170
	(0.149)	(0.150)	(0.143)
Decision Time			0.005***
			(0.001)
Decision Time^2/1000			−0.003***
			(0.001)
Constant	0.978***	0.720**	0.604**
	(0.259)	(0.281)	(0.275)
N	572	572	
Log PseudoL	−345.3	−343.1	−335.1

Parameter estimates (std. error) with *, **, and *** denoting significance at 10%, 5%, and 1%. Robust standard errors, clustered by subject.

Table 10: **Probit estimates for likelihood of optimal choice with high stakes**

4.3 Heuristics

Individuals may use simple rules for making decisions when faced with complex decisions. Such heuristics reduce cognitive requirements by focusing the decision-maker on the most promising strategies, albeit imperfectly. In this section, we estimate the degree to which subjects use four common decision rules: payoff evaluation, tallying, lexicographic ordering, and elimination of dominated options. We posit a utility function, u, which is a linear weighting of the relevant option characteristics for the four heuristics considered:

$$u_{i,o} = \beta \mathbf{X_o} + \varepsilon_{i,o}$$

where i and o denote an individual and a specific option, $\mathbf{X_o}$ is a vector of option characteristics, β is the vector of weights placed on each characteristic, and ε is some random component.

For each option, $\mathbf{X_o}$ is defined along four dimensions, all scaled between 0 and 1. First is the option's *payoff*, which controls for optimal decision making. It is the probability of payment associated with each option. Second is the *tallying* heuristic which treats all states as if they were of equal likelihood, discarding probability information (Dawes 1979). This would favor options that cover the most states. It is measured as the percentage of states covered by the option. Third is the *lexicographic* heuristic which favors options that cover the most probable state (Keeney and Raiffa 1993, Gigerenzer and Goldstein 1996). If this does not lead to a unique choice, the second most probable state is used, and so on. This heuristic performs quite well in a variety of decision environments (Payne et al. 1993). We measure the lexicographic heuristic as the percentage of most likely states that are consecutively covered by an option after ranking states by associated probabilities from largest to smallest. Fourth is the *undominated* heuristic which focuses on eliminating the least desirable options (Montgomery 1983, Hogarth and Karelaia 2005). In its simplest form, it selects only from options that do not consist of a strict subset of the states included in another option. This measure equals one if the set of states included in the option is not a subset of states included in another option and zero otherwise.

	All	18–40	41–60	>60
Payoff	3.469***	4.144***	3.767***	2.851***
	(0.313)	(0.691)	(0.530)	(0.481)
Tallying	4.843***	3.325**	5.115***	5.564***
	(0.576)	(1.116)	(0.929)	(0.988)
Lexicographic	1.869***	2.661***	1.612***	1.455***
	(0.273)	(0.554)	(0.436)	(0.468)
Undominated	0.277	0.888**	0.238	−0.026
	(0.188)	(0.419)	(0.312)	(0.297)
Observations	1016	280	376	360
LogL	−1729	−429	−639	−645

Parameter estimates (std. error) with **, *** denoting significance at 5% and 1%. Unstarred parameters are not significant at 10%.

Table 11: **Estimates of decision-making rules**

For example, consider the choice set presented in Figure 1. Our four measures for Option A are 0.66 for payoffs (summing over covered states), 0.67 for tallying (four of six states), 0 for lexicographic order (most probable state is not covered) and 1.0 for undominated. For Option D, the four measures are 0.62 for payoffs, 0.50 for tallying, 0.33 for lexicographic order (two most probable states), and 1.0 for undominated.

An individual is assumed to select the option that maximizes utility from options available in a choice set C: $u_{i,o} \geq u_{i,o'}$, $\forall o' \in C$. If ε is distributed (type 1) extreme value, the probability of selecting option $o \in C$ is given by

$$p_C(o) = \frac{e^{\beta \mathbf{X_o}}}{\sum_{o' \in C} e^{\beta \mathbf{X_{o'}}}}.$$

This yields McFadden's (1974) conditional logit model. We estimate the maximum likelihood parameters with standard errors adjusted for within-subject correlation (Wooldridge 2002). Results are reported in Table 11 for the sample as a whole and by age group.[11]

There are a number of differences across age groups. Subjects aged 40 and younger give the most weight to payoff maximization. They are also the only group that gives any significant weight to an option being undominated. As age increases, the reliance on payoffs decreases while the use of tallying increases. The youngest group places more emphasis on lexicographic

[11] As the logistic choice model cannot identify each parameter and the variance of the distribution, parameters should be interpreted as β/σ, complicating intuitive comparisons across age groups.

properties of an option than any other age group. For subjects over 60 years of age, the focus is primarily on the number of covered states. This is an optimal heuristic only when states are equally likely. For a person over 60, having an additional state covered in a 6-state task is roughly equivalent to an extra 33% chance of getting paid ($5.564 \times 1/6 \approx 2.851 \times 1/3$).[12]

Kovalchick et al. (2005) and Tanius et al. (2010) find no age effect in a variety of experiments. Tanius et al. (2009) examine decision making in a similar setup to ours, though there are significant differences between our experiments. Their experiment did not provide financial incentives for the decision task, and does not allow examination of within-subject variation. Further, their design does not allow for an objective ranking of options. In four experiments, Kovalchik et al. (2005) found little difference in decision making between older and younger subjects. They conclude that "a widely held notion, even among decision researchers, that decision making faculties decline with aging" is unfounded (pg. 90). In contrast, we find a significantly lower likelihood of selecting the optimal option as well as lower efficiency with age. These seemingly conflicting findings may suggest that aging has a differential effect on various types of decisions. Older individuals appear more often to use heuristic approaches (Johnson 1990) and use different heuristics than younger subjects. For example, older individuals are more likely to overweight low probability events and underweight high probability events (Peters et al. 2007), consistent with the tallying heuristic. Thus, it is quite possible that age does not diminish our faculties, but does change the decision-making approach. The set of experiments used by Kovalchik et al. (2005) differs substantively from our experiment with almost no role for the type of heuristics investigated here. As a result, age differences that we identify in the use of heuristics likely play no role in their experiments.

[12] As pointed out by a referee, this estimation nests the one player analogy of Quantal Response (McKelvey and Palfrey 1995, Goeree et al. 2005) by adding the three heuristics—tallying, lexicographic, and undominated. QRE would only use the expected payoff as the explanatory variable. The improved performance of the heuristic model is in part demonstrated by the significance of the three heuristics parameters. Complete QRE results are available on request.

5 Validation of Estimated Heuristics

It is reasonable to ask how robust our heuristics estimates are and if they predict behavior in a different set of tasks. To examine their validity, we conducted an additional experiment with a new set of subjects and different choices tasks. A total of 66 new subjects (34 under the age of forty and 32 over the age of sixty) participated in a validation experiment where each task involved six options and ten states. As in the main and high stakes experiments, subject invitations were stratified by age and sex. In terms of perceived difficulty, these tasks are somewhere between the 4-option 6-state task and the 13-option 10-state task in our main experiment. The experiment involved four distinct tasks, each of which appeared twice. Subjects also saw the familiarization task as in the main experiment, for a total of nine tasks. Subjects did not know tasks would be repeated and did not know that the order of tasks, states, and options was randomized. As in the main experiment, subjects were paid \$1 if the selected option contained the randomly drawn state plus a \$3 participation payment.

In addition to validating the estimated heuristics, our goal was to see if the employed heuristics allow choices to be manipulated and whether older individuals will make worse decisions and receive lower payoffs. Subjects were presented with substantially more variability in option payoffs than in the original experiment along with more variability in the number of states different options cover. In some cases, the best option had an expected payment of almost twice that of the next best alternative. The four choice tasks are shown in Table 12 where options are presented in order of expected payoffs and states are presented in order of probability. The table shows both the predicted probabilities for each age group based on our estimated heuristics in Table 11, and the actual frequencies with which each option was chosen.

In the first task, Option A covers only three states, but these states are the most probable ones. Option B is the only option to cover more than three states. We aimed to exploit the difference between a lexicographic heuristic and a tallying one, which simply counts the checkmarks. Our heuristics estimates would predict that younger subjects would select the optimal option with a 61% probability, while older subjects would select Option B with a

60% probability. In the experiment, both groups selected the optimal option with greater frequency than the heuristic model predicts. This is not wholly unexpected, given the large difference in expected payoffs and the fact that the estimates are derived from an experiment with different sizes of choice sets. Nevertheless, estimated heuristics predict the modal choice for each age group. Further, younger subjects received a much higher average payoff, defined as the sum of each option's expected payoff times its frequency of selection. Average payoff for younger subjects was 0.68 versus 0.53 for older subjects (Mann Whitney $p < 0.001$).

The second task is similar to the first, but adds more check marks to Options C through F to increase the odds of those options being selected by subjects relying on the tallying heuristic. Average payoff for younger subjects was 0.46 versus 0.39 for older subjects (Mann Whitney $p = 0.063$). Across both age groups, more individuals select Option C through F than in the first task, suggesting that the tallying heuristic can be exploited to some extent. The third task attempted to induce indifference among all options for the older age group. Options have substantially closer payoffs than in previous tasks and inferior options cover more states. Looking at actual frequencies suggests the optimal was again chosen more frequently than estimated, but significant errors among older subjects were observed. Average payoff for younger subjects was 0.67 versus 0.62 for older subjects (Mann Whitney $p = 0.006$).

The fourth task attempts to coax the younger group into selecting a suboptimal option while leading older subjects to the optimal choice. A fairly extreme choice task needs to be created for the predicted performance of older subjects to be greater than that of younger subjects. Here, the tallying heuristic does well, as the option with most states covered is optimal. The lexicographic heuristic, if applied literally, would prefer Option B. Ultimately, younger subjects did not do worse than older subjects and in fact earned a higher average payoff, 0.84 compared to 0.76 (Mann Whitney $p = 0.005$). This suggests younger subjects adjust their strategy in the new experiment and are not easy to exploit.

Overall, the older age group chose significantly worse options, on average, in all four deci-

State	PDF	Options A	B	C	D	E	F
1	32	✓		✓			
2	30	✓	✓				
3	16	✓			✓		
4	7			✓		✓	
5	6		✓			✓	✓
6	3		✓				
7	3		✓	✓			✓
8	1		✓				✓
9	1		✓		✓		
10	1		✓		✓	✓	
Expected Payoff:		78	45	42	18	14	10
Predicted Selection Probability							
Younger:		.61	.26	.08	.02	.02	.01
Older:		.26	.60	.07	.03	.03	.02
Actual Selection Frequency							
Younger:		.72	.24	.01	.01	.01	.00
Older:		.34	.50	.05	.08	.00	.03

(a) Choice Task I

State	PDF	Options A	B	C	D	E	F
1	19	✓					
2	19	✓					
3	18	✓		✓			
4	14					✓	
5	13		✓		✓		
6	9		✓		✓	✓	✓
7	5		✓	✓			✓
8	1		✓	✓	✓		✓
9	1		✓	✓	✓	✓	✓
10	1		✓	✓	✓	✓	✓
Expected Payoff:		56	30	25	26	25	17
Predicted Selection Probability							
Younger:		.50	.21	.13	.05	.09	.04
Older:		.18	.30	.15	.15	.09	.12
Actual Selection Frequency							
Younger:		.69	.04	.07	.09	.06	.04
Older:		.42	.34	.06	.05	.08	.05

(b) Choice Task II

State	PDF	Options A	B	C	D	E	F
1	31	✓	✓	✓			
2	17	✓			✓	✓	✓
3	12	✓	✓	✓	✓		✓
4	10			✓	✓	✓	
5	9		✓			✓	✓
6	8	✓	✓			✓	
7	6	✓		✓	✓		✓
8	4		✓	✓	✓	✓	✓
9	2		✓	✓	✓	✓	✓
10	1				✓	✓	✓
Expected Payoff:		74	66	65	52	51	51
Predicted Selection Probability							
Younger:		.31	.18	.18	.11	.11	.11
Older:		.16	.17	.16	.17	.17	.17
Actual Selection Frequency							
Younger:		.63	.06	.06	.07	.06	.12
Older:		.31	.11	.11	.14	.16	.17

(c) Choice Task III

State	PDF	Options A	B	C	D	E	F
1	13		✓	✓			✓
2	12	✓	✓	✓	✓		
3	11	✓	✓	✓	✓	✓	✓
4	11	✓	✓				
5	11	✓	✓		✓	✓	
6	10	✓	✓				
7	10	✓		✓		✓	✓
8	9	✓	✓			✓	
9	9	✓					
10	4	✓			✓		✓
Expected Payoff:		87	77	46	38	41	38
Predicted Selection Probability							
Younger:		.35	.59	.03	.00	.01	.01
Older:		.60	.35	.02	.01	.01	.01
Actual Selection Frequency							
Younger:		.88	.06	.03	.00	.01	.01
Older:		.67	.11	.08	.03	.06	.05

(d) Choice Task IV

Predicted selection probabilities are derived from estimates in Table 11.

Table 12: **Validation experiments**

sion tasks.[13] The experiment suggests that the design of options can be used to manipulate older subjects more easily than younger subjects. In particular, the tallying heuristic appears to be more prone to manipulation.

6 Conclusion

Individuals frequently encounter complex environments in which they have to make a decision. When selecting health insurance or retirement plans, individuals often have to consider and compare many options, each with multiple attributes. Similar challenges arise in settings ranging from selecting a cell phone plan to purchasing a car. Previous research has found that when faced with a large number of options, individuals may be less likely to make a choice or more likely to self report being dissatisfied with the choice they made. We use laboratory experiments to assess if individuals are making optimal decisions when options can be objectively evaluated.

We find that subjects are less likely to select optimal options from larger choice sets than from smaller ones. Our results indicate that performance significantly decreases with age, but does not vary with sex. Further, older subjects suffer a greater performance reduction due to an increase in the number of options. This result was replicated with another set of subjects for whom the monetary incentives for making an optimal choice were increased tenfold.

Differences in decision making across age appear to be caused by the use of different heuristics. Older subjects simply tend to count the number of positive attributes provided by each option. These tendencies were found to be robust when a different set of subjects faced a distinct set of options in a validation experiment. Of course, context-specific heuristics may complement our findings. If people learn about health insurance, specifically, over their lifetimes, the inherited knowledge may benefit older subjects, offsetting some of the decline in performance that we observe. We cannot conclude from our study the relative contribution of cognitive aging effects versus cohort differences. However, by controlling for

[13] We also compared the observed and predicted choice frequencies separately for the first and second time a subject saw each choice task. Qualitatively, there are no differences in results. Subjects are fairly consistent on a given choice task. Additionally, as with the high stakes experiment, there is no indication that the results are due to disparate education levels among age groups.

one pertinent difference between the generations—namely educational attainment—we have possibly removed one of the greatest differences between today's younger and older cohorts. Nevertheless, for policy aimed at improving decisions of today's seniors, the distinction may not be consequential.

One may be tempted to conclude that individuals are better off with fewer options, and argue for artificially limiting choice as Frank and Newhouse (2007) do. Our findings should not be interpreted as supporting this view. When the expanded choice set includes an option vastly superior to any option available with fewer choices, average efficiency may increase even if fewer individuals select the optimal option. Alternatively, a smaller share of a larger pie can be better than a larger share of a smaller pie. While our results suggest that the share will decrease as the number of options increases, the change in the size of the pie depends on the specific options that are available in the two situations. In naturally occurring settings, it may not be possible to determine if new options are better than those that previously existed.

Instead, our results serve as a reminder that one should be aware of behavioral biases while promoting choice. The theory of asymmetric paternalism (Camerer et al. 2003), for example, prescribes respecting consumer sovereignty by making all choices available, but presenting them in a fashion that encourages optimal decisions among those using less desirable heuristics. Subjects who rely on the tallying heuristic are likely to select the option that covers the most states, independent of each state's relative probability. Providing comparisons in which the probabilities of states are more or less similar allows the tallying heuristic to perform well. This could be a boon to those over 60 if, as our results suggest, they are relatively more likely to use the tallying heuristic. Decision tools that refocus decision makers on the likelihood of states might also combat the suboptimality of the tallying heuristic. Other decision tools may actually encourage bad choices. For example, a common way of presenting Medicare Part D plan options is by listing the total number of drugs covered by each plan. This may encourage sub-optimal decision making by reinforcing a tendency to ignore the likelihood of a state occurring.

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APPENDIX: Experiment Instructions and Screenshots

Screen Image 1 – Instructions

Instructions

INTRODUCTION

You are participating in an experiment on decision making. You will be paid a $3 participation fee for this experiment. At the end of the experiment you will also be paid additional money based on your decisions during the experiment. It is important that you understand the directions well since this can help you make better decisions and hence earn more money.

Each round you will be presented with a set of options. In the example to the right you have three options: A, B, and C. In each round one card will be drawn from a deck of 100 cards. If the option you selected that round includes the card drawn then you will earn an additional $1. If it does not, then you will not earn any additional money in that round.

In this example, the cards are numbered from 1 through 5 and the numbers next to the cards in the column labelled "Odds" tell you how many cards in the deck are of that type. For example, there are twenty cards in the deck with a 1, fifteen cards with a 3 and so on. This is also shown in the deck of cards below. The chance that a Card 1 is drawn is 20/100 = 20%. There will always be a total of 100 cards in all rounds, but in any given round, there may be more or less than five types of cards.

		Options		
	Odds	A select	B select	C select
Card 1	20	✓		✓
Card 2	25	✓	✓	✓
Card 3	15	✓		
Card 4	10	✓	✓	✓
Card 5	30		✓	

Example Decision

A check mark in the column under an option indicates that the option contains that particular kind of card. In the example, Option A has cards 1, 2, 3, and 4, while Option B has cards 2, 4 and 5. No two options will have the same set of cards.

Your task in each round will be to select in option. You select an option by clicking the "select" button corresponding to the option you want. When you press the "select" button, a dialog box will open asking you to confirm your choice. You may try this now by pressing the "select" button for an option in the table.

After you select an option, a card will be drawn. Suppose that a Card 3 was drawn. You would earn $1 if you had selected option A, but would not earn any money if you had selected Option B or Option C. This is because Option A has a check mark for Card 3 but Option B and Option C do not. We will now describe in detail how the process of drawing a card works.

Screen Image 2 – Instructions (continued)

DRAWING A CARD

In each round, after you select an option, you will have to draw one card from the deck of cards. Each round will have a deck of 100 cards and the "Odds" column will tell you how many cards of each type are in the deck. To the right is a sample deck of 100 cards corresponding to the example decision shown above. Recall there are 20 Card 1's, 25 Card 2's, and so on.

Before selecting a card, you will have to shuffle the cards. By clicking on the 'Shuffle' button, the cards will be turned over and shuffled. If you have not already done so, you should press the 'Shuffle' button now to see how this works.

After shuffling ends, you can click on any one card to select it. Clicking on a card will reveal the card you have drawn. If you have not already done so, you should select a card now by clicking on it. If your selected option contains the card you selected you will earn $1 for that round. If your selected option does not contain the card you chose, then you will receive no additional earnings for that round. During the process of shuffling and choosing cards you will be able to see your selected option below the deck of cards.

Once you choose a card from the shuffled deck, you will have to reveal all cards in the deck by clicking the 'Reveal All Cards' button. If you have not already done so, you may press on the 'Reveal All Cards' button now.

At this point, your results for the round would be displayed. The results panel will tell you: (1) whether your selected option contains the card you drew, (2) your winnings for the current round, and (3) your total earnings up to that round. You will then be able to press a button to proceed to the next round.

When instructed,
press the button to shuffle the cards:

Shuffle

1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3
4	4	4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5	5	5
5	5	5	5	5	5	5	5	5	5
5	5	5	5	5	5	5	5	5	5

The Deck of Cards

Please note that each round is a separate decision-making problem. You can only select one option in any round, but you can select different options in different rounds. At no time during this experiment will you be able to return and change your decision.

To sum up, this experiment consists of 9 rounds. In each round you will be presented with various options, each containing different combinations of cards. The numbers next to the cards denote how many of each card type are in the deck of 100 cards. After you pick an option, the computer shuffles the deck and you pick one card. If you select an option that contains the card randomly selected by the computer, you will earn $1. Then you move on to the next round.

READY?

To move through the experiment, you should use only the buttons provided. Do not use any of your browser's buttons ("Forward," "Back," or "Refresh") as this will void the experiment and the payment you have earned.

When you have read the instructions and are ready to proceed, press the button below.

Proceed to Experiment

Screen Image 3 – Sample Round

Decision Round

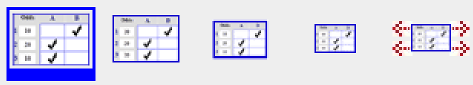
Decision Round

Please select an option from the table below.

We will determine your payment using a deck of cards as explained in the instructions. The deck of cards that applies to this decision is shown below the table of options.

Table Layout

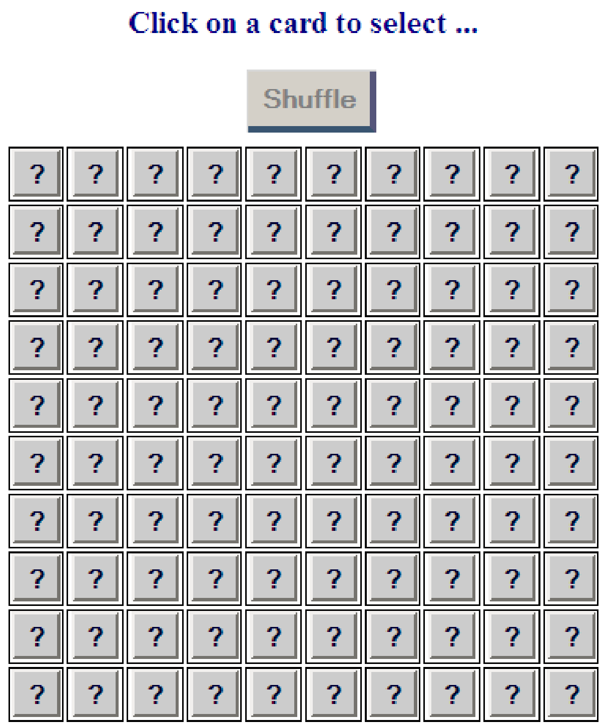
If you want to change how the table below looks on your screen, you can change the layout by clicking on one of the images below. Please note that this will not change the information in the table in any way.

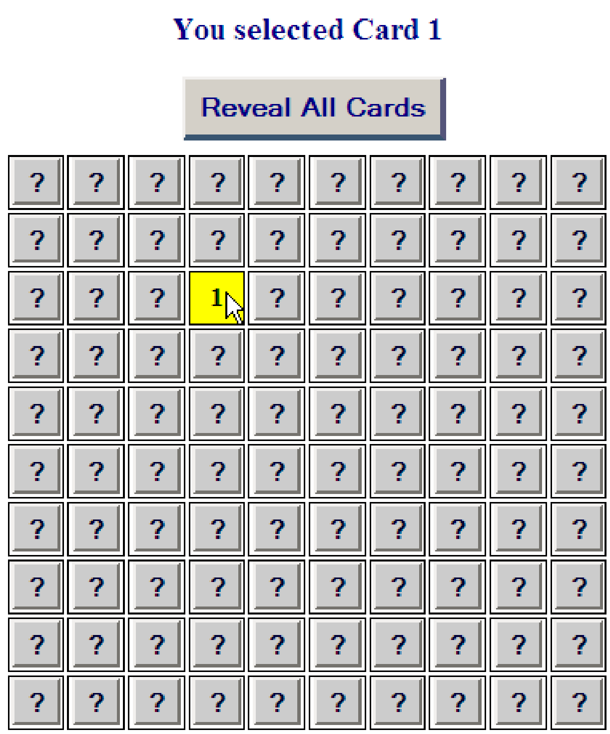


		Options			
	Odds	A select	B select	C select	D select
Card 1	21	✓	✓	✓	
Card 2	9		✓	✓	
Card 3	26	✓			✓
Card 4	12		✓	✓	✓
Card 5	24	✓		✓	✓
Card 6	8		✓		

1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1
1	2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	4	4	4	4
4	4	4	4	4	4	4	4	5	5
5	5	5	5	5	5	5	5	5	5
5	5	5	5	5	5	5	5	5	5
5	5	6	6	6	6	6	6	6	6

Screen Image 4 – Cards: Selection





Screen Image 5 – Cards: Determining Payment for Decision Round

You selected Card 1

Please continue below

3	2	5	3	5	3	4	4	1	2
4	2	6	3	1	5	3	3	3	5
2	5	1	1	4	5	1	3	3	3
2	5	2	1	6	4	1	2	3	6
5	1	3	4	5	6	2	6	3	1
4	3	1	5	4	5	5	3	3	3
2	3	5	4	3	1	1	5	1	1
1	3	5	1	5	5	6	1	4	5
3	6	4	3	5	5	5	1	6	1
1	3	3	3	5	1	5	4	3	5

	Odds	Option B
Card 1	21	✓
Card 2	9	✓
Card 3	26	
Card 4	12	✓
Card 5	24	
Card 6	8	✓

Result of round 2

Your selected option B included Card 1
Your payment for this round is $1
Your total payment through 2 rounds is $5

continue to next decision