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Abstract

We examine in controlled experiments how individuals make choices when faced with multiple options. The choice tasks mimic the selection of health insurance, prescription drug, or retirement savings plans. However, in our experiment, the available options can be objectively ranked. We find that the probability of a person selecting the optimal option declines as the number of options increases, with the decline more pronounced for older subjects. Heuristics seem to differ by age with older subjects relying more on suboptimal decision rules. Behavior consistent with the estimated decision rules is observed in an out-of-sample experiment.

JEL classification: C91, DO3, I18

Keywords: experiments, decision making, optimal choice, age effects, heuristics

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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

Individuals selecting retirement savings or medical insurance plans face a profusion of choice. This often leads to the selection of seemingly suboptimal plans (Iyengar and Kamenica 2008, Kling et al. 2008). Our objective is to better understand how individuals make complex decisions, why they sometimes make bad ones, and how these are affected by the nature of the choice task. We do so experimentally by having subjects select from choice sets with varying numbers of options. 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 be averse to choice. Faced with many options, they postpone making a decision and are likely to be unhappy with their choices.

Iyengar and Lepper (2000) show that consumers encountering a large assortment of jams or chocolates were less likely to make a purchase or express satisfaction with their choice than consumers presented with a smaller assortment. Similar patterns have been identified in more consequential decisions. Physicians offered a greater choice of drugs to prescribe are less likely to prescribe *any* drug (Redelmeier and Shafir 1995, Roswarski and Murray 2006). Enrollment in workplace retirement savings plans is sensitive to the information provided (Duflo and Saez 2003), the presence of default options (Carroll, et al. 2008), and decreases with the number of choices (Iyengar, Jiang, and Huberman 2004, Agnew and Szykman 2005).

The recent introduction of prescription drug coverage into Medicare, known as Medicare Part D, provides another example. As the new Medicare benefit was being 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 it "difficult and confusing" (Kaiser Family Foundation 2006). Heiss, McFadden, and Winter (2007) report that most of the 4.6 million Medicare recipients without prescription drug coverage would benefit from enrolling. Frank and Newhouse (2007) argue the complexity of Medicare Part D plans has discouraged enrollment and likely resulted in suboptimal choices.

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 current research by objectively measuring the optimality of subjects' decisions and by estimating the rules individuals use when making a choice. Several field experiments have attempted to estimate optimal choices from actuarial or survey methods (Heiss, McFadden, and Winter 2007, Winter et al. 2006). These approaches tend to be limited in their inability to define the full choice set or to quantify the value of each alternative for specific consumers. Schram and Sonnemans (2008) explore experimentally the effect of complexity on choice in selecting stylized health-care plans with costly information acquisition. They find the quality of decisions decreases in more complex choice sets, as does the amount of information subjects elected to consider. However, the ranking of options depended on each subject's risk preferences, a confounding factor absent from our design.

We provide subjects with a series of multi-attribute choice tasks where one option is 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 to each subject. While a correct choice always exists, its identity is concealed from subjects by manipulating both the number of attributes of each option and the number of options.

Unlike most economics experiments, our subject pool includes individuals ranging in age from 18 to over 80. While the effect of sex on decision making in economics experiments has received considerable attention (Croson and Gneezy 2008, 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 experimental tasks. In contrast, we find significant differences, and later discuss this apparent disparity. Our design allows for both analysis of the frequency of optimal choice and estimation of the decision rules used by different age groups.

Despite the economic importance of the decisions, 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 2008). Given limits on the brain's ability to retain and process information (Miller 1956 and Cowan 2001), the use of simple choice-making strategies, or heuristics, simplifies the decision. However, the cognitive powers of the human brain are not constant through life as cognitive function and working memory decline with age.[1] With age, individuals experience lower recall (Gilchrist, Cowan, and Naveh-Benjamin 2008), reduced ability to make connections (Mitchell et al. 2000), less task focus (Isella et al. 2008), and slower information processing (Cerella 1985). Perhaps as a result, older individuals appear to face greater difficulties with decisions (Frank 2004, Hanoch and Rice 2006, Hibbard et al. 2001) and are more prone to decision errors (Finucane et al. 2002). These factors lead to significant adjustments in decision-making heuristics. For instance, older individuals examine less information and consider fewer options when making choices (Cole and Balasubramanian 1993, Johnson 1993, Zwahr, Park, and Shifren 1999).

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 significant economic impacts, as total assets in 401(k) plans exceeds $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, Rettenmaier, and Wang 2007).

In our experiments, subjects make optimal choices 40% of the time across all choice tasks, with older subjects making more decision errors than younger participants. Graduate degree holders make fewer decision errors. Other levels of education do not appear to be significant, and decision errors do 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. Age has a second-order effect as well, with older subjects experiencing a greater increase in decision errors than younger subjects as the number of options increases.

We examine two possible explanations for the age effect. First, a higher stakes experiment replicates our initial findings, suggesting that economic explanations, such as search costs or wealth effects, are not a likely explanation. Second, we focus on behavioral explanations. The psychology literature identifies several common heuristics individuals use to choose among multi-attribute options. Focusing on the most prominent heuristics, we fit a combined model to our data and establish the weights each age group allocates to each

[1] See, for example, Mittenberg, Seidenburg, O'Leary, and DiGiulio 1989, MacPherson, Phillips, and Della Sala 2002, and Zelinski and Burnight 1997.

decision-making strategy. We find decision-making heuristics differ with age. Older subjects tend to discard information on the relative importance of attributes, selecting options with the largest *number* of attributes (Cole and Balasubramanian 1993, Johnson 1993, Zwahr, Park, and Shifren 1999). 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 will be needed. We design a new experiment as an out-of-sample test of the heuristics estimates. We test and verify the heuristics estimates by designing a new experiment as an out-of-sample test.

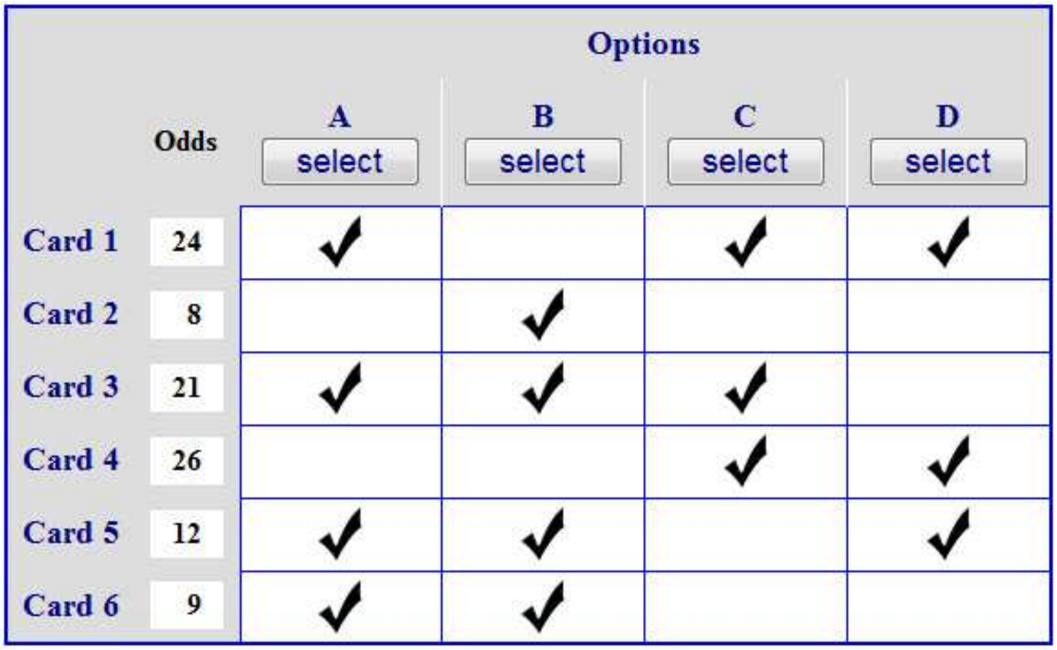
2 Experimental Design and Procedures

The experiment consists of a series of computerized choice tasks. In every task, there are a number of distinct states that could each 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.[2] 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 by columns and labeled alphabetically. Checkmarks in the Options column indicate all of the states included in that option. 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 unmarked randomly shuffled cards displayed on the screen. Once a subject draws a card by clicking on it, the number on every card is revealed. If the chosen option contains the selected state, a subject earns $1 for that round, and earns $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 one state removes considerations of risk from the problem, allowing for straightforward comparisons across subjects.

[2]Tables are relatively simple and a format often preferred by subjects (Agnew and Szykman 2005).



	Odds	A	B	C	D
		select	select	select	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 problem

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			✓	✓	✓	✓		✓			✓	✓	✓

Table 1: Experimental treatments. 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).

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 problem (though options and states are presented in random order).

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. In 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. Ten state choice sets are formed from six-state ones by splitting some states into multiple (sub)states. The probability of the new (sub)states totals that of the original state. Further, any option containing the original state also contains all of the new (sub)states while options not containing the original state contain none of the 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 problems was randomized to control for order effects. Subjects learned the results of each round 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 a two-option, three-state problem that served to familiarize subjects with the interface.

	All	Options 4	Options 13	States 6	States 10	PDF 1	PDF 2
Optimality	40%	47%	34%	42%	39%	34%	46%
Near Optimality	65%	72%	58%	65%	65%	73%	57%

Table 2: Frequency of optimal choice

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. Subjects were randomly selected for invitations, stratified by age and sex, with a response rate exceeding 70%. The average age was 50.7, with thirty five subjects under the age of 41, forty seven between 41 and 60 years of age, and forty five older than 60. Males constituted 52% of our sample. In our sample, 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. The experiment took an average of 20 minutes with subjects receiving an average payment of $9.02, including a $3 participation payment. Subjects were paid either by an online funds transfer or a mailed check.

3 Results

We begin our analysis with some general descriptive statistics of overall subject performance (see Table 2). The optimal choice (with the highest *expected* payoff) was selected in 40% of all choice tasks. We define an option as "nearly optimal" if its expected payoff is above 90% of the optimal option's payoff. Such options were selected in two thirds of all choice tasks.

Subjects made better choices more often in the 4 option problems than in the 13 option problems (see Table 2), selecting both optimal and nearly optimal options with significantly greater frequency (Wilcoxon sign-rank $p < 0.001$).[3] The performance in both cases is far greater than would be expected if subjects 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 change. Comparing the two probability distributions, optimal choices were made in 46% of the choice tasks with the extreme distribution (PDF2) compared to 34% with the more uniform distribution (PDF1) (Wilcoxon

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

	All	Age			Sex	
		18–40	41–60	>60	Women	Men
Optimality	40%	52%	40%	32%	41%	40%
Near Optimality	65%	72%	65%	60%	65%	65%
Efficiency	87%	90%	87%	84%	87%	87%
Normalized Efficiency	46%	60%	44%	36%	47%	49%
Subjects	127	35	47	45	58	69

Table 3: Choice performance by age

sign-rank $p < 0.001$). The opposite relationship holds for nearly optimal choices, though this can be attributed to the design of the choice tasks. In the 13 option choice 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. The presence of a clearly superior option led to a greater likelihood of its selection.

Overall, the summary statistics suggest (perhaps not surprisingly) that subjects have a harder time picking a needle out of a larger haystack than a smaller one. A key finding of this study is that decision making deteriorates with age. Table 3 reports performance by age and sex. An optimal choice was made in 32% of the problems faced by subjects over the age of 60 compared to 52% for those under 40 years of age. This pattern also persists across cardinal measures of performance.[4] 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 the expected payoff from random selection, and 100% corresponding to the optimal option. For all four measures, the differences between the youngest and oldest age groups are highly significant (Mann Whitney $p < 0.001$) while intermediate comparisons (youngest to middle and middle to oldest groups) are of mixed significance.[5] There are no differences in performance under any measure between women and men (Mann Whitney $p > 0.843$ for all four measures).

[4]One must be cautious in making comparisons across choice tasks for a given subject as the set of options differed, making errors more costly in some choice 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. However, our primary focus is on comparisons across subjects, for which cardinal measures of performance are valid.

[5]For Mann Whitney tests, each measure's average across all eight choice tasks was used for each subject.

	Main Experiment Only			High Stakes and Main	
	(1)	(2)	(3)	(4)	(5)
13 Option Dummy	−0.333***	−0.350***	−0.192**	−0.289***	−0.069
	(0.074)	(0.076)	(0.091)	(0.105)	(0.140)
10 State Dummy	−0.084	−0.088	−0.089	−0.150	−0.164*
	(0.071)	(0.074)	(0.074)	(0.094)	(0.097)
PDF2 Dummy	0.312***	0.324***	0.329***	0.396***	0.406***
	(0.064)	(0.066)	(0.066)	(0.095)	(0.095)
Age (Years)		−0.014***	−0.010*	−0.023***	−0.018***
		(0.005)	(0.005)	(0.004)	(0.005)
Male		−0.133	−0.155	−0.226	−0.231
		(0.143)	(0.141)	(0.145)	(0.145)
Graduate Degree		0.576***	0.621***	0.529***	0.540***
		(0.167)	(0.164)	(0.174)	(0.174)
13 Option Dummy			−0.479***		−0.449**
× Age > 60 Dummy			(0.183)		(0.216)
High Stakes Dummy				−0.116	−0.112
				(0.149)	(0.150)
Constant	−0.199**	0.491*	0.244	0.978***	0.720**
	(0.090)	(0.277)	(0.301)	(0.259)	(0.281)
N	1016	1016	1016	572	572
Log PseudoL	−668.7	−645.7	−640.8	−345.3	−343.1

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

Table 4: Probit estimates for likelihood of optimal choice

Next, we estimate a probit model to investigate how decision characteristics and subject demographics impact the selection of optimal options (see Table 4). In all specifications (see columns 1–3), 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 insignificant effect. This is most likely due to the relatively small increase in their numbers across treatments or the way in which the increase in states was implemented. However, subjects are much more likely to select the optimal option when facing a problem with the extreme probability distribution of states (PDF2), than when facing the distribution that places more equal weights on each state. PDF2 has half of the states collectively accounting for only a 5% chance of getting paid. This may indicate that a

	Optimality	Efficiency	Normalized Efficiency
Age	−0.005***	−0.002***	−0.007***
	(0.002)	(0.001)	(0.002)
Male	−0.050	-0.015	−0.058
	(0.051)	(0.019)	(0.073)
Graduate Degree	0.213***	0.082***	0.314***
	(0.067)	(0.025)	(0.095)
Constant	0.656***	0.947***	0.796***
	(0.093)	(0.034)	(0.131)
R-squared	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 5: OLS estimates of efficiency and demographics

reduction in the number of *salient* states improves performance.

Specification (1) includes only the main effects of our design. In specification (2), we include demographic variables. Age has a negative and highly significant impact on the likelihood an individual will select the optimal option. There is no significant difference between men and women in the ability to select the optimal option. We find that postgraduate education has a positive and significant impact.[6]

Motivated by the effect of age, we examine the interaction between options and age by adding a dummy variable for our oldest age group facing 13 option problems. 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.

Our dependent variable, optimality, may be viewed as a crude measure of performance, failing to account for differential costs of errors. Consequently, we explore cardinal performance measures in Table 5. Since options differ across tasks, it would be inappropriate to compare these efficiency measures across tasks, but it is a reasonable exercise across subjects. We focus on demographic factors, and present OLS results for our two efficiency measures. Our dependent variable is the average efficiency or average normalized efficiency for each sub-

[6] We only present results with a postgraduate education dummy as inclusion of 'some college education' and 'college degree' dummies produce similar results with neither 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 ($p = 0.003$).

ject across all eight choice tasks. For comparison, we also present OLS results for optimality, where the dependent variable is the percentage of choice tasks in which a subject selected the optimal option. All measures again show no effect for sex and a significant positive effect for postgraduate education. For all measures, we observe a significant negative effect for age.

We examine two possible explanations for the differences in behavior across age groups. The first explanation, grounded in economic motives, is that older subjects may be wealthier on average, and thus may be less sensitive to the incentives provided in the experiment. A second explanation is that either cognitive ability or the problem-solving approach change with age. We consider each of these in turn.

4 High Stakes

To investigate the role of wealth effects and evaluate if performance improves with remuneration, we conducted an additional set of experiments. We employed a fractional factorial design, selecting four of the eight original choice tasks with stakes ten times those used in the main experiment.[7] Subjects were paid $10 per round 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 choice tasks as our main experiment keeps the difficulty of the problem constant while significantly increasing the costs of decision errors. Thus, explanations rooted in wealth effects would predict an improvement in decision making.

A total of 63 new subjects were recruited for the high stakes experiment, with thirty two under the age of 40 and thirty one over the age of 60 with a desire to contrast the oldest with the youngest subjects. Subjects took an average of 13 minutes for the entire experiment and earned an average of $28.50. Higher stakes did 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 lower stakes experiment (Mann Whitney $p = 0.028$).[8] However, despite spending more time choosing, subjects generally did not make better choices.

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

[8] The salience of stakes is arguably dictated not by overall earnings, but by the potential improvement in payoffs from better decision making. The expected difference in earnings between a subject who selects the worst option in each choice task and one who selects the best option is $18. Given 59 seconds, on average, for each of the four choice tasks, this equates to an hourly wage of $275.

	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 6: High stakes experiment summary statistics

Summary statistics for the high stakes experiment and the four corresponding choice tasks in the main experiment are presented in Table 6. 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).

We pool the low-stakes and high-stakes data in our probit specification, introducing a dummy variable for the high stakes treatment. We present two specifications in the last two columns of Table 4.[9] 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. In both specifications, the coefficient on the high stakes dummy is negative but not significant ($p > .438$ for both specifications). These results suggest that performance does not improve in the high stakes experiment.

5 Heuristics

Individuals may use simple rules for decision making when faced with complex decisions. Such heuristics reduce cognitive requirements by focusing the decision-maker on the most promising strategies, albeit imperfectly (Kahneman and Tversky 1979). 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.

[9]We also replicated our analysis of Table 4 and Table 5 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 rounds while the main experiment had eight, it is possible that the main experiment allowed for more learning. To check this, we ran the analysis in Table 4 columns (4) and (5) using corresponding choice tasks from the main experiment only when they occurred in the first four rounds. This does not change our findings.

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 attributes. 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 is measured as the percentage of 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 heuristic allows for evaluation of choices even when the utility of each attribute (or subjective probability of each state) is not known (Aksoy, Cooil, and Lurie 2008). 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.

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 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

	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 7: Estimates of decision-making rules

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

This yields McFadden's conditional logit model (1974). We estimate the maximum likelihood parameters, with standard errors adjusted for within-subject correlation (Wooldridge 2002). Results are reported in Table 7 for the sample as a whole and by age group.[10]

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 upon payoff decreases while the use of tallying increases. The youngest group places more emphasis on the lexicographic properties of an option than any other age group. This heuristic performs quite well in a variety of decision environments (Payne, Bettman, and Johnson 1993). 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 six-state problem is roughly equivalent to an extra 33% chance of getting paid ($5.564 \times 1/6 \approx 2.851 \times 1/3$).

In a series of experiments, Kovalchik et al. (2005) found little difference in decision making between older and younger subjects. Kovalchik et al. conclude that "a widely held notion, even among decision researchers, that decision making faculties decline with aging" is unfounded (p. 90). In contrast, we note a significantly lower likelihood of selecting the optimal

[10] 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.

option 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. Hence, the age differences that we identify in the use of heuristics likely play no role in their experiments.

It is reasonable to ask how robust these estimates are and if they predict subject behavior in a different set of choice tasks. To determine this, we conducted additional experiments with a new set of subjects and different choices tasks.

5.1 Out-of-Sample Experiment

A total of 66 new subjects (34 under the age of forty and 32 over the age of sixty) participated in the out-of-sample experiment. Each choice task involved 6 options and 10 states. The experiment involved four distinct tasks, each of which appeared twice, plus a practice task as in the main experiments. Subjects did not know that tasks would be repeated and did not know that the order of tasks, states, and options were 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 estimates, our goal is to see if the employed heuristics allow choices to be manipulated. In this experiment, subjects were presented with substantially more variability in option payoffs than in the original experiment. 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 8. Options are presented in order of expected payoffs and states are presented in order of probability. Subjects, of course, saw options and states in random order, and were not provided the expected payoff. The table also shows both the predicted probabilities for each age group based on our estimated heuristics in Table 7, and the actual frequencies with which each option was chosen.[11]

[11] 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.

State	PDF	A	B	C	D	E	F
		Options					
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	A	B	C	D	E	F
		Options					
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	A	B	C	D	E	F
		Options					
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	A	B	C	D	E	F
		Options					
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

Table 8: Out-of-sample experiments.
Predicted selection probabilities are derived from estimates in Table 7.

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. We predicted 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 payoffs and the fact that the estimates are derived from an experiment with different sizes of choice sets. Nevertheless, the estimated heuristics predict the modal choice for each age group. Further, younger subjects received a much higher expected 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 makes the PDF slightly more uniform and adds more check marks to Options C through F. Average payoff for younger subjects was 0.46 versus 0.39 for older subjects (Mann Whitney $p = 0.063$). The third task attempted to induce indifference among all options for the older age group. Options have substantially closer payoffs than in previous choice 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 the older subjects to be greater than that of the 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 expected payoff (.84 compared to .76, Mann Whitney $p = 0.005$). This suggests younger subjects adjust their strategy in the new experiment and are not easy to exploit. Conversely, while older subjects did better than predicted, the heuristics estimation provides an accurate qualitative description of their decision-making. The older group is more prone to suboptimal decision-making and is more easily exploited by manipulating the presentation of the decision.

Overall, the results show that the estimated heuristics parameters predict behavior well in out-of-sample problems.

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 multiple 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. The differences in decision making across age appear to be caused by the use of different heuristics. Older subjects tend simply to count the number of positive attributes provided by each option. These tendencies were found to be robust when another set of subjects faced a distinct set of options in a third experiment.

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. 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 many naturally occurring settings, it is not possible to know if new options are better than those that previously existed. Who knows a priori if a new flavor of jelly will be preferred to existing flavors? Even if the creation of this flavor causes some not to buy jelly, this loss could be offset by the gain others receive from a new preferred option.

Instead, our results serve as a reminder that one should be aware of behavioral biases while encouraging 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 would be a boon to those over 60 who are more likely to use the tallying heuristic, according to our results. 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

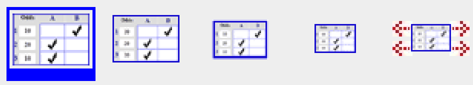
Decision Round

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

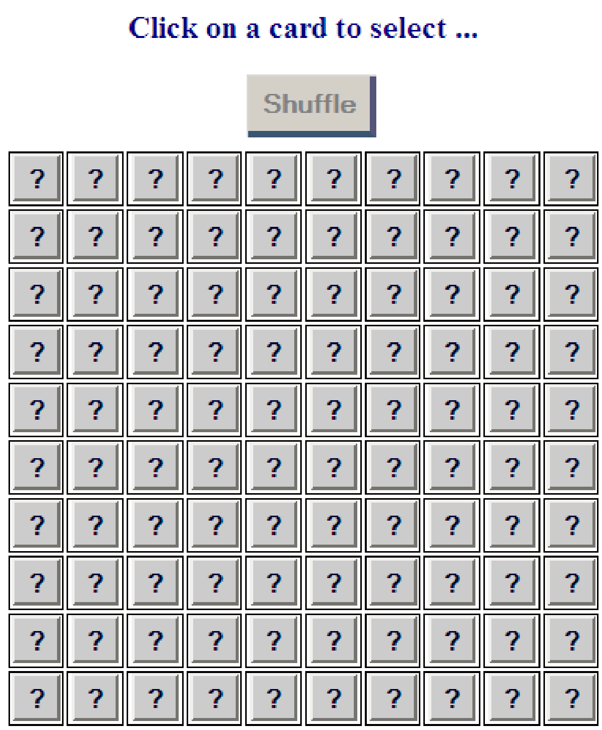
If you want to change how the table below looks on your screen, you can change the layout by clicking on one of the images below. Please note that this will not change the information in the table in any way.

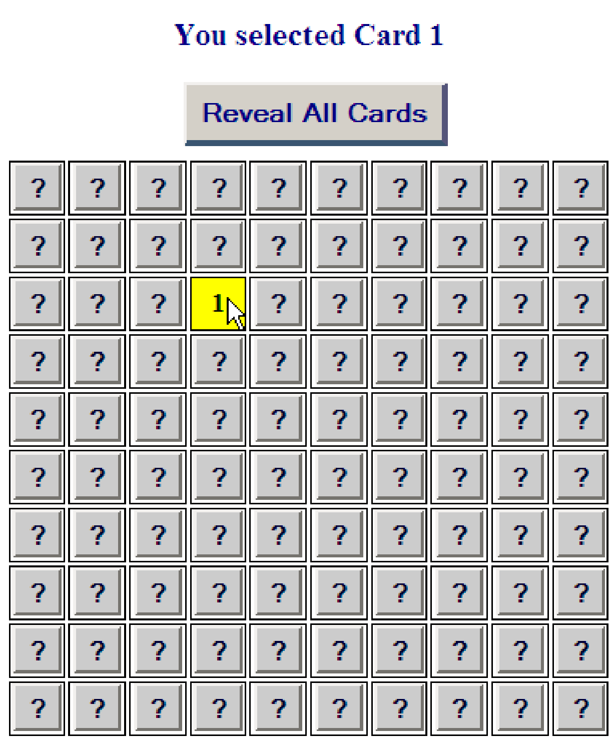


		Options			
	Odds	A select	B select	C select	D select
Card 1	21	✓	✓	✓	
Card 2	9		✓	✓	
Card 3	26	✓			✓
Card 4	12		✓	✓	✓
Card 5	24	✓		✓	✓
Card 6	8		✓		

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