The Influence of Positive and Negative Framed Information Load: An Experimental Investigation

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The purpose of this paper is to test the effect of three information attributes—the framing of information as positive or negative, the symmetry and non-symmetry of information sets, and the quantity of information on individual choices—when choosing between two lotteries. The main effects from a random effects probit model indicate that the quantity of information and symmetry of information influence individual choices over lotteries. When presented with negative information, individuals exhibit less switching behavior between two lotteries. One possible explanation for our result is that a negativity bias is present when information is framed negative which causes individuals to behave differently across lotteries regardless of the quantity of information.

INTRODUCTION

Prior research has explored how quantity of information (Eppler & Mengis, 2004; Grether & Wilde, 1983; Iyengar & Kamenica, 2010) or the type of information (Huber, et al., 1982; Kahneman & Tversky, 1979) influence choices. The traditional thought about information load is that individuals are able to make use of appropriate information and make better, informed choices. Alternatively, individuals may be subject to overload, which may result in suboptimal decision-making. The literature on information overload is extensive (see review in Eppler & Mengis, 2004). The purpose of this study is to examine whether the quantity of information or the type affect individuals' choices. Specifically, we examine the influence of two information attributes on individuals' choices over two lotteries with varying information loads. The two attributes are: (1) positive and negative framed information sets; and (2) symmetric versus non-symmetric information sets. We contribute to the literature by examining the effect of both the load and type of information being delivered.

In an effort to answer this question we use the experimental lab to evaluate the decisions subjects make under varying levels of information—2, 4, 6, 8 or 10 pieces of information in the form of a compound lottery, when information is symmetric or non-symmetric across choices, and when information is framed as either positive or negative. Our experimental design allows for a within treatment comparison. Results from a random effects probit indicate that information load and symmetry are positively related to choosing a particular lottery. We also use a random effects probit to examine whether individuals switch lottery choices as a function of information. We find that individuals stay the course—are more likely to make consistent lottery choices—when information is negative.

LITERATURE

Empirical evidence has shown that the quantity of information an individual receives correlates with their choices. Eppler and Mengis (2004) conduct a relatively recent extensive literature review of information load on decision accuracy across numerous business disciplines. They find evidence for an inverted-U relationship between decision accuracy and information load, where the optimal information threshold can vary across individuals.

Information load has been explored in laboratory and field experiments (Agnew & Szykman, 2005; Iyengar & Kamenica, 2010; Schram & Sonnemans, 2011) and in stated preference surveys (Hoehn, et al., 2010; Mazzotta & Opaluch, 1995). Information load has also been studied in numerous contexts, including marketing (Verbeke, 2005), capital markets (Paredes, 2003), investment plans (Agnew & Szykman, 2005), stated preference demand functions (Frör, 2008; Mazzotta & Opaluch, 1995), and health insurance plans (Schram & Sonnemans, 2011). As noted previously, increases in information load have been found to decrease decision accuracy (Mazzotta & Opaluch, 1995; Schram & Sonnemans, 2011), yet also increase choice variance (Mazzotta & Opaluch, 1995) and decision time (Schram & Sonnemans, 2011). Hoehn et al. (2010) find that different format presentations of the same information load can impact both the decision consistency and the error variance. Information overload tends to increase the frequency that individuals will choose the default choice or the popular choice (Agnew & Szykman, 2005, Sasaki, et al., 2011).

The disadvantages of large information sets may be so extreme that individuals may make decisions without a full examination of all available options (Caplin, et al., 2011). Iyengar and Kamenica (2010) found that individuals prefer simpler, easy-to-understand lottery choice sets over more complex lottery choice sets. In this manuscript, we use information load, information set and quantity of information interchangeably. They all refer to the amount of information provided an individual in the decision making process.

It is well-established in the literature that language used to frame a decision outcome influences our decisions. Framing is powerful because it determines people's focus and the decision outcome. Thus, in our study, we employ a negative frame treatment based on the idea that individuals are loss averse. Loss aversion implies that when an individual wins money, they feel a certain amount of pleasure, and when they lose money of the same magnitude, (s)he feels displeasure, yet the displeasure is larger than the pleasure from the gain. The idea gained prominence with Kahneman and Tversky (1979). Since then, the idea of loss aversion has been analyzed in many settings (Fryer, et al., 2012; Engström, et al., 2015; Karle, Kirchsteiger, & Peitz, 2015; List, 2003; Pope & Schweitzer, 2011; Fehr & Goette, 2007; Genesove & Mayer, 2001). We expect to find a differential response to negative compared to positive information.

As part of our lottery choices, we also explore how subjects respond with dissimilar information sets. Information that is similar across choices may be difficult to process. On the other hand, differences in information sets may assist the decision making process. Agnew and Szykman (2005) find that individuals become more overloaded the more similar the choice of retirement savings plans. We expect individuals in our study to respond to dissimilar (non-symmetric) information in the form of a dominant lottery with a higher expected value.

MODEL

Consider a risk-averse agent choosing between two policies, *X* and *Y,* where *X* and *Y* have two or more possible outcomes. Policy *X* is characterized by:

$$X = \tau * x_1 + (1 - \tau) * x_2 \quad (1)$$

where $0 < \tau < 1$, and $x_1, x_2 > 0$, representing two states of nature for policy *X*. The term τ is the probability x_1 will occur. Policy *Y* is characterized by:

$$Y = p * y_1 + (1 - p) * y_2 \quad (2)$$

where $0 < p < 1$, and $y_1, y_2 > 0$, representing two states of nature for policy *Y*. The term p is the probability y_1 will occur. In our study, we represent policies *X* and *Y* as lotteries. The agent exhibits von Neumann-Morgenstern expected utility preferences over the two policies, such that preferences satisfy the four axioms of expected utility theory—completeness, transitivity, continuity and independence.

Now consider the influence of information on an individual's preference ordering. Similar to Grether and Wilde (1983) we model information as a lottery, lottery $C_{r,s}$. In our study, information load is defined by the number of lotteries added to $C_{r,s}$. Isolating an individual's response to information load requires controlling the content or quality of information. The quality of information (*r*) is defined by the mean and variance of lottery $C_{r,s}$, which is held constant across all information sets. Since the quality of lottery $C_{r,s}$ is held constant, for ease of exposition and to better isolate the influence of information quantity, we simplify notation to C_s. An information set containing two pieces of information can be written as:

$$C_2 = \pi * c_1 + (1 - \pi) * c_2 \quad (3)$$

where c_1 and c_2 represent the two prizes available in lottery C_2 and π represents the probability of winning prize c_1 such that $0 < \pi < 1$. An information set with four pieces of information is:

$$C_4 = \gamma * c_1 + \theta * c_1 + \left(\frac{1}{2} - \gamma\right) * c_2 + \left(\frac{1}{2} - \theta\right) * c_2 \quad (4)$$

where $\pi = \gamma + \theta$ and are probabilities bound between 0 and 1. Holding quality constant, it follows that the value of lottery C_s is equivalent across different levels of information such that $V(C_j) = V(C_k) \forall j, k$, where *j* and *k* refer to varying quantities of information (i.e., C_2 and C_4 have the same mean and variance).

We combine the same information lottery C_s with lottery *X* and *Y* to create two symmetric compound lotteries, X_{C_s} and Y_{C_s}.

Lottery X_{C_s} is:

$$X_{C_s} = (1 - \delta) * X + \delta * C_s \quad (5)$$

and lottery Y_{C_s}:

$$Y_{C_s} = (1 - \delta) * Y + \delta * C_s \quad (6)$$

The δ term is bound between 0 and 1 and is the relative weight placed on lottery *C* within the compound lottery.

To capture the influence of negative frame within the pairwise choices, we multiply the prizes in C_s by –1 for both lottery *X* and *Y (*see equations 5 and 6). *A priori*, and based on expected utility theory, we expect no differences in behavior between positive and negative frames. However, there is significant evidence people respond differently when presented with negative frames relative to positive frames (Kahneman & Tversky, 1979).

To understand the influence of information non-symmetry, we add a positive real integer L to *Cs*. C_s + L is added to lottery *X* while only C_s is added to lottery *Y*, thus creating non-symmetry. By choosing an appropriate value for L, we construct a pair of lottery choices so that a portion of the people who initially choose lottery *Y* will now choose *X*. Specific details are provided in the experimental design section.

Finally, we explore how improving negative information (i.e., reducing the size of a negative outcome) may influence an individual's lottery choice. As before, we do this by multiplying the prizes in C_s by –1 for lotteries *X* and *Y*, but now the integer L is then added to the information for lottery *X*, but not *Y*. Essentially, this treatment mimics the ability of adding positive information to a negative information set to see if people will switch.

Each of these four treatments is varied over five information load conditions. A more detailed description of these conditions is contained in the experimental design section. The following null hypotheses test the effect of our treatment variables—quantity of information, information frame, and symmetry–on individuals' lottery choices.

H1. Quantity of information does not impact lottery choice

H2: Information framing as positive or negative does not impact lottery choice

H3: Non-Symmetry of information does not impact lottery choice.

A priori we expect that individuals are more likely to pick a particular lottery, and not switch between lotteries, as information load increases and when the information is framed negative. However, when information is non-symmetric, we do expect to see some individuals respond positively to the new information lottery that has a higher mean or expected value.

EXPERIMENT DESIGN

Our experiment followed standard procedures. Fifty-six participants were recruited from introductory general education courses within the college of business to participate in three sessions. Subjects were informed the experiment would take less than sixty minutes and average earnings would be between $10 and $20, yet subjects could earn less. Realized average earnings in the experiment were $29.67 with a maximum of $57.75 and a minimum of $4.00. No participation bonus, i.e., a fixed payment amount, was guaranteed. All earnings were based on experimental choices. Earnings were paid in cash at the end of the experiment and were paid in a private neighboring room. Participants were asked to arrive in a designated classroom during a specified time interval. Each participant was greeted by the experiment administrator and provided one-on-one guidance in establishing a private login and password to access the computerized experiment interface. Participant privacy and anonymity was provided by seating participants at distant computers, typically separated by several computers in the same row, or by seating the participants in rows (14 feet apart) with their backs to each other. Once the subjects had created a login, they proceeded to the experiment using their unique login. The experiment commenced with a standard introduction about earnings and rules (e.g., do not talk with others, turn off cell phone, etc.). Next, subjects were provided an example of making a choice between two lottery options and how earnings would be determined by a random draw (which were all computer generated using a random number generator). Following the example, subjects were prompted to engage in several practice rounds complete with a random number draw and payout information if the round had been played for real money. There was no time constraint or limit on practice rounds, yet all participants completed the entire experiment within 30 minutes. For every choice exercise, a simple, 4-function calculator was provided on the computer screen with a tally of cumulative earnings and a progress bar which indicated the proportion of the experiment completed. An experiment administrator was available to answer questions.

Following practice rounds, subjects proceeded to the controlled experiment followed by a survey to collect individual and demographic information. Complete instructions are available upon request. The experiment begins with a multiple price list (MPL) risk exercise adapted from Holt and Laury (2002). We adjust the payoffs used in Holt and Laury's MPL by multiplying all payoffs by a factor of 5 (see Table 1 for the MPL used) to ensure that prize values maintain dominance. Subjects are presented with ten choice sets across two lotteries: lottery *X* and lottery *Y*. Like Holt and Laury (2002) the prize values for lottery *X* and lottery *Y* are held constant across all choice sets, while the probabilities change systematically as subjects move through the choice sets from choice set one to choice set ten. Subjects are instructed to choose either lottery *X* or lottery *Y* for each of the 10 choice sets. The expectation is for subjects to choose lottery *X* initially when there is a larger probability of winning the lower prizes of $10 or $0.50, and then switch from lottery *X* to lottery *Y* at a particular choice set when there is a greater probability of earning the larger amount in each lottery ($10 and $19.25, respectively), and thus choose lottery *Y* for all following choice sets. The switch from *X* to *Y* reveals the subject's risk preferences. If a subject chooses to switch to *Y* at choice set (exercise) 9, for example, rather than a previous exercise, (s)he is revealing that (s)he is fairly risk averse and not willing to take even a small chance of earning only $0.50.

TABLE 1
HOLT AND LAURY MPL LOTTERIES

Exercise		Option X	Option Y
1	o X o Y	A 10% chance of earning \$10.00 and a 90% chance of earning \$8.00	A 10% chance of earning \$19.25 and a 90% chance of earning \$0.50
2	o X o Y	A 20% chance of earning \$10.00 and a 80% chance of earning \$8.00	A 20% chance of earning \$19.25 and a 80% chance of earning \$0.50
3	o X o Y	A 30% chance of earning \$10.00 and a 70% chance of earning \$8.00	A 30% chance of earning \$19.25 and a 70% chance of earning \$0.50
4	o X o Y	A 40% chance of earning \$10.00 and a 60% chance of earning \$8.00	A 40% chance of earning \$19.25 and a 60% chance of earning \$0.50
5	o X o Y	A 50% chance of earning \$10.00 and a 50% chance of earning \$8.00	A 50% chance of earning \$19.25 and a 50% chance of earning \$0.50
6	o X o Y	A 60% chance of earning \$10.00 and a 40% chance of earning \$8.00	A 60% chance of earning \$19.25 and a 40% chance of earning \$0.50
7	o X o Y	A 70% chance of earning \$10.00 and a 30% chance of earning \$8.00	A 70% chance of earning \$19.25 and a 30% chance of earning \$0.50
8	o X o Y	A 80% chance of earning \$10.00 and a 20% chance of earning \$8.00	A 80% chance of earning \$19.25 and a 20% chance of earning \$0.50
9	o X o Y	A 90% chance of earning \$10.00 and a 10% chance of earning \$8.00	A 90% chance of earning \$19.25 and a 10% chance of earning \$0.50
10	o X o Y	A 100% chance of earning \$10.00	A 100% chance of earning \$19.25

Subjects then proceed to the payout portion where one of the ten lottery choice sets is randomly selected and played for real money, all of which are displayed on the computer screen (i.e., the random number, the winning payoff, and accumulated earnings). For example, suppose lottery exercise seven is randomly selected. This lottery is then played where a subject who chose lottery *X* will earn \$8 with a 30% probability or \$10 with 70% probability, and a subject who chose lottery *Y* will earn \$0.50 with 30% probability or \$19.25 with 70% probability.

In this experiment, the switching point from the MPL establishes a baseline lottery for the influence of information load. We provide additional information to respondents in the form of compound lotteries as described in the model section (i.e., *Cs*) based on their baseline switching point. If an individual chose option *X* for the first four decisions and then switches to *Y* at the fifth decision, all subsequent lotteries in the experiment will be based on the fifth lottery. For subjects with more than one switching point, the first switch to lottery *Y* is used as the baseline lottery. The baseline represents a person's risk preferences and provides an opportunity to control for risk.

TABLE 2
INFORMATION TREATMENTS

Treatment	Quality of Information	Compound Lottery	Framing	Five levels of information[a]
Treatment 1	**Symmetric**	C	Gain in earnings	{2, 4, 6, 8, 10}
Treatment 2	**Non-symmetric**	$C + L$	Gain in earnings	{2, 4, 6, 8, 10}
Treatment 3	**Symmetric**	$-C$	Loss in earnings	{2, 4, 6, 8, 10}
Treatment 4	**Non-symmetric**	$-C + L$	Loss in earnings	{2, 4, 6, 8, 10}

[a] An information load of 2 indicates that an additional compound lottery with two possible outcomes is added to the baseline lotteries of X and Y. An information load of 4 indicates that additional compound lottery with 4 possible outcomes is added to the baseline lotteries of X and Y, etc.

Next, we construct four treatment sets to evaluate the influence of information attributes on decisions. The treatment sets are formed by crossing the two information symmetry conditions (symmetric v. non-symmetric) with two information frame conditions (positive v. negative). The treatment sets are: (1) Symmetric positive frame; (2) Non-symmetric positive frame; (3) Symmetric negative frame; and (4) Non-symmetric negative frame. Each treatment set is varied over five information load conditions for a total of 20 lottery choice exercises that were randomly presented to subjects. The treatment sets are described below and presented in Table 2, and the compound lottery prizes are presented in Table 3.

Symmetric Positive Frame. We create compound lotteries by combining an identical information lottery C_s to each of the lotteries in the baseline choice set (see equations 5 and 6). In lottery C_s there is a forty percent chance of winning \$6 and a sixty percent chance of winning \$16. The relevance of lottery C_s relative to lottery X and lottery Y is measured by δ, such that $0 < \delta < 1$. Throughout this experiment we set $\delta = 0.10$ so that lottery X and lottery Y maintain a dominant presence in the compound lotteries. Any value for δ could be set, and it becomes an empirical question to determine how sensitive subjects are to the choice of δ. Table 4 presents a full list of pairwise choices with 4 pieces of information for the ninth baseline lottery. Treatment set 1 is considered symmetric information because the mean and variance of the information component (C) for the two lottery choices are identical.

Non-symmetric Positive Frame. We create a non-symmetric positive framed treatment by combining C_s + L to lottery X while only C_s is added to lottery Y. We set the value of $L = 5$ based on pretest results. In Table 4, treatment set 2 is considered non-symmetric information because the mean and variance of the information components are different across lotteries X and Y.

Symmetric Negative Frame. We create symmetric negative framed information by multiplying the prizes in C_s by -1. This negative information is then added to both lotteries X and Y. In Table 4, treatment set 3 is considered symmetric information because the mean and variance of the information component for the two lottery choices are identical.

TABLE 3
COMPOUND LOTTERY VALUES

Positively Framed Compound Lotteries	C [Low gain, High gain] [\$6, \$16]	C + L [Low gain, High gain] [\$11, \$21]
Negatively Framed Compound Lotteries	$-C$ [Low loss, High loss] [–\$6, –\$16]	$-C$ + L [Low loss, High loss] [–\$1, –\$11]

TABLE 4
EXAMPLE OF INFORMATION TREATMENT SETS FOR FOUR PIECES OF INFORMATION RESULTS

Treatment Set 1: Symmetric Positive Frame		
Choose I or II	Option I	Option II
o Option I o Option II	81% chance of earning $10 9% chance of earning $8 1.6% chance of earning $6 2.4% chance of earning $16 2.4% chance of earning $6 3.6% chance of earning $16	81% chance of earning $19.25 9% chance of earning $0.50 1.6% chance of earning $6 2.4% chance of earning $16 2.4% chance of earning $6 3.6% chance of earning $16
Treatment Set 2: Non-symmetric Positive Frame		
Choose I or II	Option I	Option II
o Option I o Option II	81% chance of earning $10 9% chance of earning $8 1.6% chance of earning $11 2.4% chance of earning $21 2.4% chance of earning $11 3.6% chance of earning $21	81% chance of earning $19.25 9% chance of earning $0.50 1.6% chance of earning $6 2.4% chance of earning $16 2.4% chance of earning $6 3.6% chance of earning $16
Treatment Set 3: Symmetric Negative Frame		
Choose I or II	Option I	Option II
o Option I o Option II	81% chance of earning $10 9% chance of earning $8 1.6% chance of earning –$6 2.4% chance of earning –$16 2.4% chance of earning –$6 3.6% chance of earning –$16	81% chance of earning $19.25 9% chance of earning $0.50 1.6% chance of earning –$6 2.4% chance of earning –$16 2.4% chance of earning –$6 3.6% chance of earning –$16
Treatment Set 4: Non-symmetric Negative Frame		
Choose I or II	Option I	Option II
o Option I o Option II	81% chance of earning $10 9% chance of earning $8 1.6% chance of earning –$1 2.4% chance of earning –$11 2.4% chance of earning –$1 3.6% chance of earning –$11	81% chance of earning $19.25 9% chance of earning $0.50 1.6% chance of earning –$6 2.4% chance of earning –$16 2.4% chance of earning –$6 3.6% chance of earning –$16

Non-symmetric Negative Frame. We create non-symmetric negative information by multiplying the prizes in C_s by –1 for lotteries *X* and *Y*. The integer L is then added to the information for lottery *X*, but not lottery *Y*. We again set the value of $L = 5$ (see Table 3). In Table 4, treatment set 4 is considered non-symmetric information because the mean and variance of the information components are not the same for lotteries *X* and *Y*.

For each treatment set, individuals make pairwise choices for an information load with 2, 4, 6, 8 and 10 pieces of information (see Table 2), for a total of twenty compound lottery choice exercises. To control for ordering effects, the twenty lottery choice sets were computer randomized, with each individual encountering the twenty choices in a different order. This experimental design allows for a within treatment comparison of information load, information frame, and information symmetry on individual decisions.

TABLE 5
SAMPLE CHARACTERISTICS

	Mean	Standard Deviation
Male	0.732	0.447
Age	22.607	9.328
Credit Hours	13.500	2.264
Hours Worked per Week (outside job)	17.464	14.057
Wage	9.992	9.308
Number of Kids	0.464	1.144
Experiment earnings	29.68	11.906
Question Time (seconds)	12.558	13.275
Business Major	0.5536	0.502
Math (calculus and / or statistics)	0.5893	0.496
Risk	0.0061	0.760
Number of participants	56	
Number of decisions	1120	

RESULTS

Fifty-six subjects participated in a within treatment experiment across five distinct levels of information, two levels of frame (positive and negative), and two levels of information type (symmetric and non-symmetric). Sample characteristics are presented in Table 5. Individuals participated in 20 lottery choice exercises for a total of 1,120 individual-lottery level decisions.

Participants were recruited from a general economics course for non-majors and business statistics courses. From Table 5 we see the sample was 73% male with average age of 22.6 years. Our subjects carried 13.5 credit hours, worked 17.5 hours per week, and made $9.99 per hour, on average. The majority of participants, 55 percent, were from business degree programs.

Risk is assigned based on the individual's baseline lottery. The higher the baseline lottery, the more risk averse. Table 6 provides statistics on baseline lottery decisions. Roughly, 80% of participants switched between lotteries 4 and lotteries 8. Assuming CRRA, most of our subjects are risk neutral to risk averse (Holt & Laury, 2002). Assuming CRRA for money, the utility function is $u(x) = x^{1-r}$. The switch points provide an interval estimate for a subjects coefficient of risk aversion. When $r = 0$, a subject is risk averse; when $r < 0$, a subject is risk loving; and when $r > 0$, a subject is risk averse. The payoffs are set such that risk neutrality occurs at the 4th lottery choice, and risk aversion thereafter (see Holt & Laury, 2002).

TABLE 6
BASELINE LOTTERY

Lottery	Frequency	Percent
1	3	5.36
2	1	1.79
3	3	5.36
4	6	10.71
5	12	21.43
6	8	14.29
7	11	19.64
8	8	14.29
9	2	3.57
10	2	3.57

TABLE 7
PROPORTION SWITCHING FROM *Y* TO *X*

56 Subjects	Treatment				
Information	1 (Positive, Symmetric)	2 (Positive, Non-symmetric)	3 (Negative, Symmetric)	4 (Negative, Non-symmetric)	224 observations
2	0.000	0.304	0.089	0.304	0.174
4	0.107	0.161	0.179	0.089	0.134
6	0.125	0.107	0.071	0.036	0.085
8	0.054	0.179	0.107	0.071	0.103
10	0.161	0.054	0.089	0.089	0.098
280 observations	0.089	0.161	0.107	0.118	0.119

The proportion of subjects switching from *Y* to *X* by treatment and information quantity is presented in Table 7. It appears that the switching behavior occurs primarily in the non-symmetric information treatments (2 and 4). Formal regression analysis will allow us to test for main effects. In order to test our three hypotheses about the effect of treatment variables on individual's lottery choice, we estimate two random effects probit models to model the utility maximizing choice of individual *i*

The random effects are at the individual level and capture income effects of the accumulation of previous earnings in the experiment. Ordering and learning effects are controlled for through random ordering of lotteries for each individual during the experiment. The two models differ in their dependent variable. The first dependent variable is an indicator variable that equals one when a person chooses lottery *Y*, and zero otherwise. The second dependent variable equals one when an individual deviates from their lottery choice within the treatment sets indicated in Table 2, and zero otherwise.

TABLE 8A
TEST OF MAIN EFFECTS WITH DEPENDENT VARIABLE = 1 IF INDIVIDUAL CHOOSES Y

Variable	Degrees of Freedom	Value of Chi-Square Test Statistic	p-value
Quantity of Information	4	12.02	0.0172
Frame of Information	1	0.11	0.7360
Symmetry of Information	1	28.09	< 0.0001

TABLE 8B
TEST OF MAIN EFFECTS WITH DEPENDENT VARIABLE = 1 IF SWITCHES LOTTERY CHOICE WITHIN TREATMENT SET

Variable	Degrees of Freedom	Value of Chi-Square Test Statistic	p-value
Quantity of Information	4	1.15	0.7649
Frame of Information	1	2.87	0.0905
Symmetry of Information	1	1.13	0.2869

TABLE 9
MARGINAL EFFECTS FOR FINAL LOTTERY CHOICE

	Dep. Var. = 1 if Person Chose lottery Y	Dep. Var. = 1 if Person Switched Lotteries within Treatment
Quantity of Information = 4	-0.056	
	[0.038]	
Quantity of Information = 6	-0.016	0.004
	[0.041]	[0.032]
Quantity of Information = 8	0.018	0.014
	[0.044]	[0.037]
Quantity of Information =10	0.068	0.033
	[0.047]	[0.038]
Negative Frame	-0.020	-0.056*
	[0.040][a]	[0.032]
Non-Symmetric Information	-0.240***	-0.032
	[0.046]	[0.034]
n	1120	896

* p<.1, ** p<.05, *** p<.01.
[a] Delta method standard errors in square brackets.

For example if an individual chooses *X* with two pieces of information, then *Y* with four pieces of information, then the indicator equals one. Because our dependent variable in this model is based on a switch within treatment, the first observation in each treatment must be dropped (i.e. it is not possible to switch if you have not yet made a decision). The independent variables include demographic variables (listed in Table 5) along with indicators that represent our experimental design.

The experiment is a 5 × 2 × 2 fully interacted design. The influence of information is tested by performing a test for the main effect of the quantity of information (see Table 8a; full probit results are available upon request). The p-value for the test is 0.0172. We reject **H1** at the five percent level. The quantity of information appears to influence lottery choice, yet individually, the marginal effects of specific information quantities are insignificant (see Table 9). Another way to analyze individual choice is to examine whether treatment variables are related to a person deciding to switch their lottery choice from *Y* to *X* or from *X* to *Y*. Referring to Table 8b, when the dependent variable indicates a deviation between lottery choices within a treatment, the main effect is insignificant as well as marginal effects.

We test for the main effect of frame on lottery decisions using the same empirical set-up. The p-value for the test is 0.7360. We fail to reject **H2**. There is no evidence to suggest that frame (e.g., losses versus gains) influences lottery choice. A test for main effects when the dependent variable indicates a switch suggests that the frame of information is significant at the ten percent level (see Table 8b). The marginal effects presented in Table 9 show that subjects are less likely to switch when the frame is negative.

We also test for the main effect of non-symmetry. The p-value for the test is < 0.0001. We reject **H3**. There is evidence to suggest that the non-symmetry of information affects lottery choice. Individuals are significantly less likely to choose lottery *Y* when the information is non-symmetric (see Table 9), and appear to stay the course. This result is not surprising. The information lotteries C + L (or $-C$ + L) added to lottery *X* are more attractive than lotteries C_s added to lottery *Y*.

DISCUSSION

We propose two possible explanations for why individuals are more likely to make consistent choices when facing negative information: (1) negativity bias; and (2) loss aversion. First, the negativity bias implies people respond more intensively to negative information than they respond to positive information of equal magnitude (Ito, et al., 1998; Rozin & Royzman, 2001; Sonsino, 2011). Further, McGraw et al. (2010) find that people respond differently to loss-loss comparisons than they respond to gain-gain comparisons. The relative comparison of a loss against another loss is not the same as the relative comparison of a gain against another gain (McGraw, et al., 2010). What this may suggest is that if subjects are more sensitive to loss-loss comparisons (as they would be in a negative framed lottery) then they will be more aware of differences across lotteries and therefore make more consistent choices.

Second, when positive payoffs are combined and compared against negative payoffs, loss aversion exists (McGraw, et al., 2010). In our negative framed treatments, negative payoffs were combined with our positive payoff baseline lottery creating the potential for loss aversion to impact peoples' choice decisions over lotteries (Kahneman & Tversky, 1979). Individuals who primarily focus on negative information relative to the positive lottery are more affected by loss aversion (Harinck, et al., 2012). This enhanced effect may have amplified the decision to stay on course, resulting in people making more consistent choices.

With respect to information symmetry, Huber et al. (1982) find that when one information set clearly dominates the alternative, people will be more likely to choose the dominant set. In our treatments for non-symmetric information sets, people would be more likely to choose lottery *X* over lottery *Y* regardless of the level of information because the information set for lottery *X* clearly dominates the information set for lottery *Y*.

Helgeson and Ursic (1993) find choice accuracy increases the less similar the information sets; thus, we would expect to see less switching behavior when information sets are non-symmetric. This may imply that they are able to make more accurate and consistent decisions. We do indeed find a negative relationship, though it is statistically insignificant.

CONCLUSION

We used experimental methods to investigate the influence of information load, frame, and quality on choice consistency. The results show that information load and symmetry affect decision consistency. Individuals are also more likely to make consistent lottery choices when information is negative. A negativity bias may exist which increases the attractiveness of one choice relative to the other and increases the likelihood individuals will make consistent choices regardless of the information load. The results are conditional on the relative weight given to the informational sets. In this study, the baseline lotteries maintained dominance. Future work could consider modifying the relative weight (i.e., the value for δ) given to the informational sets.

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