Measuring Ambiguity Aversion*

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Abstract

We investigate attitudes toward uncertainty using a new instrument with gambles for substantial stakes. We focus on the evaluation of gambles involving known (the probability and payoff are precise) and unknown (ambiguity in the probability and/or payoff) uncertainty. Several features of our instrument are notable. First, subjects make choices for different levels of ambiguity over probabilities, over payoffs, and decisions involving ambiguity over probabilities and payoffs simultaneously. Second, we measure preferences at different base probability levels allowing us to explore systematic variations in aversion for different levels of underlying uncertainty over both possible gains and possible losses. Third, we use two different frames, describing the gambles as a "lotteries" or as "investments / insurance" decisions. Finally, our design avoids informational asymmetries between the subject and the experimenter, as the level of information for the experimenter and subjects is equal throughout the experiment. Any missing information in the ambiguous gambles is unavailable to all, rendering the gambles 'unknowable' in the terminology of Chow and Sarin (2002). Our findings indicate that the subjects are ambiguity averse. The nature of this aversion differs depending on whether the gambles involve gains or losses.

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1. Introduction

One of the fundamental problems in the study of decision making is the analysis of choices under uncertainty, especially when the probabilities or payoffs to an event are unknown. Choices involving uncertain events can generally be classified in two categories: risky events and ambiguous events. A risky event is an event that is typically thought of as having a clear probability for a given outcome. For instance, a 10% chance at winning a prize of $50 in a raffle. Ambiguous events encompass a greater degree of uncertainty. This would include not only being unsure of the outcome of an event, but also not being sure of the probability of an event or the payoff associated with an event. Consider the question, "What is the chance that the transmission in your car will break in the next year, and how much will it cost to fix it?" In this case, neither the exact probability of breakdown nor the exact cost of the repair are known, though a decision-maker may have some idea of the range of probabilities or payoffs. Many day-to-day decisions have these properties. As Heath and Tversky (1991) note, "The potential significance of ambiguity…stems from its relevance to the evaluation of evidence in the real world."

One of the first papers to address ambiguity in decision-making was that of Knight (1921), where he distinguished between measurable, with precise probabilities, and unmeasurable, with unknown probabilities, uncertainty.[1] Little was written over the next few decades involving the role of ambiguity as it was viewed that Knight's distinctions did not play a role in decision theory (see Savage, 1954). However, the advent of the Ellsberg paradox reintroduced the importance of ambiguity in affecting decision-making. (Ellsberg, 1961) This sparked an increase in experimental research regarding attitudes toward uncertainty. Early works include Becker and Brownson (1964) and Slovic and Tversky (1974), which found evidence of ambiguity aversion. Over the last 15 years, a number of works have focused on explanations for ambiguity aversion, such as the comparative ignorance hypothesis proposed by Heath and Tversky (1991), which was extended in Fox and Tversky (1995), and by the evaluability hypothesis of Hsee, Blount, Lowenstein, and Bazerman (1999). Recent works by Chow and Sarin (2001) and Fox and Weber (2002) delve further into the comparative ignorance hypothesis. Chow and Sarin (2002) provide three classifications of uncertainty: known, unknown, and unknowable. The known case is similar to that of Knight's measurable uncertainty; all of the information regarding probabilities is known and precise. The unknown case involves ambiguity yet there is an individual or source other than the decision-maker with additional information regarding the ambiguity, and this is known by the decision-maker. Unknowable uncertainty pertains to ambiguous events where the decision-maker has as much information as anyone else regarding the uncertainty.

In this paper we investigate attitudes toward a particular type of ambiguity, where the probability distributions over the unknown parameter of the decision are known. This 'weak' ambiguity is the simplest form of ambiguity. We explore ambiguity not only in the probability of an event, but also in the outcome and in situations that involve ambiguity in the probability and outcome simultaneously. We use a new instrument designed to measure attitudes toward uncertainty in gamble choices, where the precise gambles are similar to the known uncertainty and the ambiguous gambles are comparable to the unknowable uncertainty mentioned in the previous paragraph. The subjects complete a series of choice tasks in precise (known) and ambiguous (unknowable) settings involving gambles for substantial financial stakes.

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[1] Our paper addresses a somewhat different distinction. In our experiments the uncertainty is not unmeasurable, but rather the probability distribution over the unknown probability is known. Under this form of "weak" ambiguity

In all cases the distribution of the unknown parameter is given in a way that is transparent for the subjects. We include gambles at three different underlying probabilities (10, 50 and 90 percent), over gains and losses, and in two different decision frames (abstract and investment/insurance). The instrument and additional aspects of the experimental design are explained in the next section.

The remainder of the paper is organized as follows. Section 2 presents the instrument used for measuring attitudes toward uncertainty. Section 3 contains the experimental design and procedures. Section 4 provides the results of our experiment and a comparison of our findings with other works. We conclude with a summary and discussion.

2. An instrument for measuring attitudes toward uncertainty

We have developed a new instrument for measuring attitudes toward precise and ambiguous gambles for monetary stakes. Our goals with this instrument include ensuring that the subjects understand the mechanism (or nature) driving the ambiguity and that they know that the experimenter does not have any informational advantage over the subjects regarding the outcome of the gamble. The subjects are not only informed of the range of the ambiguity but also the second order, or underlying, distribution of the ambiguous aspect of the gamble. The use of this "weak" ambiguity effectively creates a range of possible expected values for the gamble. In our experiments, the distribution of the unknown parameter is uniform. The payment procedure is described in detail to subjects prior to their making any decisions, and makes clear to subjects the distribution over possible probabilities or payoffs.

Our instrument is notably different from other instruments used to measure preferences toward precise and ambiguous gambles. The ambiguity mechanism of Powell and Ansic (1997)

probabilities are still measurable, but less transparent to the decision maker.

involves the use of five different charts with possible distributions of outcomes. In Schubert et al (2000), an ambiguous gamble is represented by two precise gambles with an equal likelihood of occurrence where a precise gamble involves receiving a large sum with a certain probability, p, and a smaller sum with probability 1-p. This type of weak ambiguity does not appear to be as transparent as that used in our experiment. Other studies differ from ours in the asymmetry of information between the experimenter and the subject. Hogarth and Kunreuther (1989) implement ambiguity through a comment regarding the certainty of the probability of an event. After stating the probability of loss, the unambiguous situation involves a statement regarding "feeling confident" about the probability. In the ambiguous situation the subject should "experience considerable uncertainty." Di Mauro and Maffioletti (1996) state how they chose to keep the subjects in the 'dark' about how the ambiguity will be resolved. Eisenberger and Weber (1995) implement ambiguity through an Ellsberg urn or past stock prices for a bank. In these cases the experimenter has full information about the ambiguity: she knows the balls in the urn and the previous stock price. This asymmetry of information between the subjects and the experimenter is not present in our experiment.

The importance of there being similar information states between the experimenter and the subject should be noted. Fox and Tversky (1991) proposed the comparative ignorance hypothesis, which states that, "…ambiguity aversion is produced by a comparison with less ambiguous events or with more knowledgeable individuals." In the experiments described in the previous paragraphs, it is evident that the experimenter is knowledgeable of the exact nature of the ambiguity while the subjects are not. This may affect how the subjects view the gamble and therefore their valuations. Indeed, Chow and Sarin (2002) find that this asymmetry alone can significantly affect valuations. They write, "If the experimenter knows the probability, the comparative ignorance effect is more pronounced and the subjects are reluctant to bet." It is possible that such an asymmetry may cause subjects to lower their valuations of an ambiguous gamble, not because of the ambiguity, but rather because they think they are playing against a rigged game. Regarding the Ellsberg scenario, Dawes, Grankvist, and Leland (2000) note that, "…the problem might not be a concern about ambiguity so much as a concern about a 'stacked deck.'" We have attempted to eliminate this information asymmetry, or stacked deck, by designing our instrument so that the level of information regarding any uncertainty is the same between the subjects and experimenter throughout the experiment.

Our measure involves a series of choices between a gamble and a certain amount. Each choice involves a tradeoff between two types of choices in a decision sheet, modeled after the choice sheets developed in Holt and Laury (2002). In Table 1 we show one such decision sheet with ambiguity in probabilities. For each Decision, the subjects must choose between Option A and Option B. Note that Option A is constant for all decisions, and has an expected value of $25.00, while option B is a certain amount ranging from $16 for Decision 1 to $35 for Decision 20. For each decision sheet, Option B changes in $1 increments. Only an extremely ambiguity-averse person would prefer Option B at the top of the sheet, and only an extremely ambiguity-seeking person would prefer option A at Decision 20. While each sheet appears to involve numerous decisions, this is not really the case. The point where subjects cross over from preferring Option A to preferring Option B provides a measure of the subject's valuation of the gamble. By comparing similar sheets with the same underlying probability of winning and payoff with varying degrees and types of ambiguity, i.e. expected values, we can measure subjects' aversion to uncertainty.

Table 1. A sample decision sheet with ambiguity in the probability

	Option A	Option B	Your Choice A or B
Decision 1	45-55% chance at winning $50	$16.00	
Decision 2	45-55% chance at winning $50	$17.00	
Decision 3	45-55% chance at winning $50	$18.00	
Decision 4	45-55% chance at winning $50	$19.00	
Decision 5	45-55% chance at winning $50	$20.00	
Decision 6	45-55% chance at winning $50	$21.00	
Decision 7	45-55% chance at winning $50	$22.00	
Decision 8	45-55% chance at winning $50	$23.00	
Decision 9	45-55% chance at winning $50	$24.00	
Decision 10	45-55% chance at winning $50	$25.00	
Decision 11	45-55% chance at winning $50	$26.00	
Decision 12	45-55% chance at winning $50	$27.00	
Decision 13	45-55% chance at winning $50	$28.00	
Decision 14	45-55% chance at winning $50	$29.00	
Decision 15	45-55% chance at winning $50	$30.00	
Decision 16	45-55% chance at winning $50	$31.00	
Decision 17	45-55% chance at winning $50	$32.00	
Decision 18	45-55% chance at winning $50	$33.00	
Decision 19	45-55% chance at winning $50	$34.00	
Decision 20	45-55% chance at winning $50	$35.00	

Decision used:__________ Die Throw:__________ Your Earnings:__________

Subjects complete a series of sheets, where the underlying probability, the range over probabilities, the range over payoffs, and ranges over probabilities and payoffs simultaneously are varied. The full set of decision sheets is summarized in Table 2. For example, the sample decision sheet shown in Table 1 appears as sheet 10 in the gain domain of Table 2. The Option A choice consists of a 45-55 percent chance of winning a prize of $50. The Option B choice, the certain alternative, ranges from $16 for Decision 1 to $35 for Decision 20. The structure of the instrument prevents the subjects from stating certainty equivalents outside of a reasonable standard. For instance, there is no opportunity for a subject to state a certainty equivalent of greater than $50 for a gamble with a prize of $50. Our instrument measures preferences at three different base probability levels: 10, 50, and 90 percent. This allows us to explore systematic variations in aversion for different levels of underlying uncertainty.

As mentioned earlier, we use discrete uniform distributions as the second order distributions in the gambles involving weak ambiguity. To operationalize the ranges, the subject draws a chip from a box that contains 1 chip for each number in the range. For instance, in the example in Table 1 the box contains 11 chips: a chip for 45 percent, another for 46 percent, and so on through 55 percent. The subjects are informed in the instructions that there is only one chip for each number in a range and that this means that each chip has an equal likelihood of being drawn. Additionally, they are informed that they may inspect any box to verify the chips. The subjects also roll two ten sided dice to determine the outcome of a gamble. We conduct examples of winning and losing gambles, along with allowing the subjects to ask questions, to ensure that the subjects understand the nature of the ambiguity. Once all decisions are made, one decision is randomly selected for each subject for payment.

Table 2. Experimental design: Decision sheets

Gain Domain (abstract and investment):				
	Option A choice		**Option B choice:** Choice Range	
Decision sheet	Probability (%)	Prize ($)	Minimum ($)	Maximum ($)
1	10	50	1	20
2	5-15	50	1	20
3	0-20	50	1	20
4	10	45-55	1	20
5	10	40-60	1	20
6	5-15	45-55	1	20
7	10	0-100	1	20
8	10	25-75	1	20
9	50	50	16	35
10	45-55	50	16	35
11	50	45-55	16	35
12	45-55	45-55	16	35
13	90	50	31	50
14	85-95	50	31	50
15	80-100	50	31	50
16	90	45-55	31	50
17	90	40-60	31	50
18	85-95	45-55	31	50
19	90	47-53	31	50
20	90	44-56	31	50

Loss Domain (abstract and insurance):				
	Option A choice		**Option B choice:** Choice Range	
Decision sheet	Probability (%)	Prize ($)	Minimum ($)	Maximum ($)
1	10	50	1	20
2	5-15	50	1	20
3	0-20	50	1	20
4	10	45-55	1	20
5	10	40-60	1	20
6	5-15	45-55	1	20
7	10	47-53	1	20
8	10	44-56	1	20
9	50	50	16	35
10	45-55	50	16	35
11	50	45-55	16	35
12	45-55	45-55	16	35
13	90	50	31	50
14	85-95	50	31	50
15	80-100	50	31	50
16	90	45-55	31	50
17	90	40-60	31	50
18	85-95	45-55	31	50
19	90	0-100	31	50
20	90	25-75	31	50

Because neither the subject nor the experimenter knows the actual values of the ambiguous variables, our design avoids asymmetry of information between the subject and the experimenter. However, we cannot be certain that the subjects do, in fact, believe that there is no informational asymmetry. Therefore this instrument is an approximation.

3. Experimental design and procedure

Our design elicits subjects' certainty equivalents using the instrument described above. The treatment combinations used in our experimental design vary the decision frame, and are shown in Table 3. Subjects complete either Set A or Set B of the decision sheets. Each set uses one of two different frames, describing the gambles as abstract "lotteries" or as "investments/insurance" decisions. Each subject completes a full set of decision sheets, giving valuations for precise (known) and ambiguous (unknowable) gambles over both possible gains and possible losses, which allows us to explore asymmetries in preferences relative to a reference point. We refer to the case of lotteries as the *abstract treatment* and the investment and insurance decisions as the *context treatment*.

Table 3. Experimental design: Treatment combinations

Treatment	Precise	Ambiguity in Probabilities	Ambiguity in Payment	Ambiguity in Probabilities and Payment
Abstract: Gain	Set A	Set A	Set A	Set A
Abstract: Loss	Set A	Set A	Set A	Set A
Investment	Set B	Set B	Set B	Set B
Insurance	Set B	Set B	Set B	Set B

Furthermore, the subjects face four different types of information in both decision frames and treatments. The 'precise' information frame has exact probabilities and exact payments stated. In the 'ambiguity in probability' frames, the probability is stated as a range and the payment is fixed. Conversely, in the 'ambiguity in payment' frames, the probability is fixed and the payment is stated as a range. Finally, in the 'ambiguity in probability and payment' frames, ranges are stated for both the probabilities and payments.

Two pre-test sessions were conducted in Principles of Economics classes at Virginia Tech; 65 students participated in these sessions. Six laboratory sessions were conducted with 84 volunteer subjects recruited from other Principles of Economics classes. Table 4 shows the number of participants and average payment for the pre-tests and for each laboratory session.

Table 4. Number of participants and average payment for each session

Session	Abstract Lotteries	Context Invest/Insure	Average* Payment
Pre-test 1	29		$26.90
Pre-test 2		36	$34.70
Lab 1	15		$26.27
Lab 2		12	$32.58
Lab 3		13	$19.85
Lab 4	14		$31.79
Lab 5		15	$31.40
Lab 6	15		$34.00
Totals	73	76	$29.67

*Calculations for the average payments for the pre-test sessions are based on the payments received by the 10 students selected to be paid from each of these sessions.

In the pre-test sessions, after consent forms were distributed and completed, instructions and forms were distributed, illustrated on an overhead projector, and read aloud by the experimenters.[2] The experimenters also simulated the procedure and payment method by completing an experiment in the front of the room. In the simulation, one of the experimenters acted as if she was participating in the experiment by completing an example decision sheet on a transparency and then drawing the appropriate chips to clarify the ambiguity, i.e., she drew a chip to determine the exact percentage out of the range of possible percentages. She then rolled the dice to determine the outcome. This was done in plain view of the subjects. After the demonstration, we informed the subjects that they could inspect any of the ambiguity devices (boxes of chips) or the dice. The decision sheets were distributed in a randomized order that was the same for all participants. At the end of the experiment, the experimenter drew 10 subject numbers for payment and the rest were allowed to leave. These 10 subjects each chose a chip to determine the gamble played, rolled a die to select a decision, and then played that decision. They were then paid their earnings in private.

In the six laboratory sessions, which took place at the Laboratory for the Study of Human Thought and Action (LSHTA) at Virginia Tech, all of the participants received a $5 payment for showing up and were paid for one of their own decisions chosen at random. The experimental procedure used in the laboratory sessions was otherwise identical to that used in the pretest sessions. Subjects played their decisions and were also paid in private.

The expected average payment to each subject for his or her decision is $25, in addition to a show up payment for those subjects attending the LSHTA sessions of $5. Actual average payment for the pretest sessions, for the 20 students who were chosen to be paid, was $30.80. The actual average payment for the laboratory sessions was $29.40, which includes the $5 show up payment. Each session lasted approximately 1 hour and 20 minutes.

4. Results

4.1. Descriptive Results

We first present aggregate data by the level of uncertainty, for gains and losses, pooled over the decision frames. Table 5 contains the average valuations for a subset of the gambles. The asterisks, next to some of the valuations for gambles involving ambiguity, indicate whether the valuation is significantly different from the precise (or known) gamble at each level of

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[2] Instructions are provided in the appendix for the context treatment with the insurance decisions conducted first.

probability.[3] Consider the winning gambles, where the valuations represent the average minimum selling price for each of the gambles. Note that for each of the probability levels, the precise gambles have the highest minimum selling price suggesting an aversion to ambiguity. Aversions to ambiguity in probability, payoff, and both probability and payoff simultaneously are evident in the low and high probability gambles. For the midrange gamble, ambiguity aversion is significant for the gamble involving dual ambiguity.

Table 5. Average valuations of gambles by ambiguity levels for gains and losses (pooled over decision frames)

Minimum Selling Price for WINNING GAMBLES			
	Payoff		
Probability	$50	$45-55	$40-60
10%	10.19	9.79*	10.12
5-15%	9.42**	9.21***	.
0-20%	8.42***	.	.
50%	24.11	24.14	.
45-55%	23.94	23.01***	.
90%	41.56	40.98*	40.53***
85-95%	39.54***	40.16***	.
80-100%	40.75**	.	.
Willingness to Pay to Avoid LOSING GAMBLES			
	Payoff (losses)		
Probability	$50	$45-55	$40-60
10%	9.55	9.51	9.74
5-15%	9.99*	10.17*	.
0-20%	10.69***	.	.
50%	26.52	25.94*	.
45-55%	25.95*	25.46***	.
90%	41.26	41.05	40.60**
85-95%	41.14	40.85**	.
80-100%	40.47***	.	.

Notes: *** indicates significance at 1 percent.
** indicates significance at 5 percent.
* indicates significance at 10 percent.

[3] One-sided means tests.

The valuations presented in the loss domain represent the maximum willingness to pay to avoid the gamble. There is not such a clear aversion to ambiguity in the loss domain as was evident for gambles for gains. There does appear to be ambiguity aversion for low probabilities of loss as the valuations increase with increases in ambiguity. However, the subjects appear to prefer ambiguity for the midrange and high probability of loss gambles. For these gambles the willingness to pay decreases as the level of ambiguity increases.

In both domains, the subjects significantly overvalue low probability events (gambles with expected values of +/- $5) and undervalue high probability events (gambles with expected values of +/- $45). However, there is evidence that the subjects undervalue midrange events in the gain domain and overvalue these events in the loss domain (gambles with expected values of +/- $25).

Table 6 presents the mean valuations for this subset of gambles for each of the treatments separately[4]. Similar patterns of ambiguity aversion in the gain domain are revealed. As for the loss domain, we again see an aversion to ambiguity for small probabilities of loss but evidence of ambiguity seeking for the midrange and high probabilities in both contexts. There appears to be evidence of a context effect in the gain domain. The minimum selling prices are higher for the gambles framed as "investments". In the loss domain, the context effect appears reversed as the valuations for the "gambles" are on average greater than those for "insurance" for low and midrange probabilities of loss. The valuations are similar in both contexts for high probabilities, however.[5]

[4] As in Table 5, the asterisks indicate whether the valuation is significantly different from the precise gamble at each level of probability.
[5] Tables containing the average valuations for all of the gambles are included in the appendix.

Table 6. Average valuations by decision frame

CONTEXT

INVESTMENT

Probability	Payoff $50	$45-55	$40-60
10%	10.78	9.74**	10.43
5-15%	9.53**	9.53**	.
0-20%	7.92***	.	.
50%	24.58	24.82	.
45-55%	25.11	23.28***	.
90%	42.22	42.03	41.88
85-95%	40.55***	41.07**	.
80-100%	41.62	.	.

INSURANCE

Probability	Payoff $50	$45-55	$40-60
10%	8.75	8.96	8.90
5-15%	9.30	9.71	.
0-20%	9.93**	.	.
50%	26.00	25.33	.
45-55%	25.69	25.29**	.
90%	41.39	41.23	39.99***
85-95%	41.13	40.21***	.
80-100%	40.68	.	.

ABSTRACT

WINNING GAMBLES

Probability	Payoff $50	$45-55	$40-60
10%	9.60	9.84	9.81
5-15%	9.32	8.89*	.
0-20%	8.90*	.	.
50%	23.64	23.45	.
45-55%	22.76**	22.73**	.
90%	40.90	39.92	39.17***
85-95%	38.48***	39.22***	.
80-100%	39.88**	.	.

LOSING GAMBLES

Probability	Payoff $50	$45-55	$40-60
10%	10.35	10.05	10.58
5-15%	10.68	10.63	.
0-20%	11.44**	.	.
50%	27.01	26.56	.
45-55%	26.22**	25.62***	.
90%	41.11	40.88	41.21
85-95%	41.15	41.45	.
80-100%	40.25***	.	.

4.2. Regression analysis

The analysis in the previous section provides some insight into attitudes toward uncertainty in a general sense. However, a considerably larger number of valuations were given as subjects offered values for all of the gambles listed in Table 2. In this section, we attempt to control for additional factors and determine whether the introduction of weak ambiguity, in the probability, payoff, or both, has any significant effect on the valuations. Since each individual gives a number of valuations, the data are dependent. We therefore use random effects regression models, which allow us to control for individual effects.

The variables used in the regression analysis are defined in Table 7. While the majority of the variables are straightforward in their interpretation, some clarification of the *Range* variable is useful. This variable is a measure of the “size” of the ambiguity for a gamble. For example, a gamble involving a 0-20% at winning $50 has an expected value (EV) of $5. However, the ambiguity introduces a range of possible expected values from a minimum of 0% chance at $50 (EV=$0) to a maximum of a 20% chance of $50 (EV=$10). The *Range* variable takes a value of 10 in this example; the difference between the minimum and maximum possible expected values ($0 to 10).[6] Gambles that do not involve ambiguity, for instance a 50% chance at $50, have *Range* values of zero.

[6] A second example: An 85-95% chance at losing $45-55 has a minimum possible EV of -$38.25 (85%*-$45) and a maximum EV of -$52.25 (95%*-$55). The *Range* is 14 in this example.

Table 7. Description of variables in regression models

VALUATION	The minimum selling price for gambles in the gain domain and willingness to pay to avoid gambles in the loss domain.
Context	= 1 if context (investment/insurance) treatment = 0 if abstract (lotteries) treatment
Range	Measure of "size" of the ambiguity from range of possible EVs. (ex. A gamble of a 0-20% chance at $50 has a range of EVs of $0-10. The value of Range is therefore 10.)
Probability	= 1 if ambiguity in the probability only of the gamble = 0 otherwise
Payoff	= 1 if ambiguity in the payoff only of the gamble = 0 otherwise
Both	= 1 if ambiguity in the probability and the payoff of the gamble = 0 otherwise

Table 8 reports results from econometric models estimated separately for gains and losses.[7] A model is estimated at each expected value to investigate if there are significant differences in valuations between precise and ambiguous gambles after controlling for context effects. Additionally, these models examine the roles of size and location of ambiguity on affecting valuations. The dependent variable in each model is the subjects' valuations. This is a positive value in the gain domain as it is indicative of willingness-to-accept and a negative value in the loss domain as it represents willingness-to-pay to avoid possible losses. Hausman test statistics and the associated p-values are presented for each model.[8]

[7] Wald tests were conducted to see if the absolute value of the constant terms, for each absolute expected value, are equal in both domains. The p-values of the test for the gambles with an expected value of +/- $5 is 0.662 and for gambles with an expected value of +/- $45 is 0.219. We cannot reject the null hypothesis that the absolute value of the coefficients are equal at any reasonable level of significance. However, the p-value for the test of gambles with an expected value of +/- $25 is 0.000. These results suggest that base valuations are similar, in absolute terms, for low and high probability gambles but not for mid probability gambles.

[8] The Hausman test compares the estimator of a consistent model, eg. a fixed-effects model, with that of a more efficient model, eg. the random-effects model. A significant test statistic indicates that the independent variables and the random effects are correlated. For more information see Hausman (1978) and Kennedy (1992).

The gain domain

The positive constants for each model in this domain are as expected. The constant of 9.956 for gambles with an expected value of $5 suggests risk seeking behavior for low probabilities of winning. The value of 40.629 for gambles with an expected value of $45 suggests risk aversion for high probabilities of winning.[9]

Table 8. Random effects models. The dependent variable is the VALUATION of each gamble.

	GAIN						**LOSS**					
Exp. Value	**5**		**25**		**45**		**-5**		**-25**		**-45**	
Constant	9.956	***	23.483	***	40.629	***	-10.198	***	-26.866	***	-41.342	***
	(0.554)		(0.549)		(0.580)		(0.627)		(0.558)		(0.537)	
Context	0.330		1.312	**	1.902	***	1.389	*	0.841		0.131	
	(0.704)		(0.706)		(0.705)		(0.796)		(0.716)		(0.668)	
Range	0.000		-0.111	***	0.023		-0.158	**	0.104	***	-0.013	**
	(0.039)		(0.036)		(0.035)		(0.078)		(0.038)		(0.005)	
Probability	-1.224	***	0.374		-1.684	***	0.306		0.097		0.549	*
	(0.428)		(0.314)		(0.472)		(0.679)		(0.332)		(0.332)	
Payoff	-0.127		0.566	**	-1.216	**	0.111		0.058		0.585	*
	(0.327)		(0.311)		(0.551)		(0.346)		(0.326)		(0.354)	
Both	-0.943	**			-1.775	***	0.344				0.616	
	(0.432)				(0.668)		(0.618)				(0.389)	
Loglikelihood	-2822.6		-1620.0		-3033.4		-2922.1		-1589.1		-2826.4	
No. of obs.[10]	1034		580		1041		1031		563		1024	
Hausman stat.	8.97		0.09		2.51		1.07		0.03		1.13	
p-value	0.0619		0.9935		0.6428		0.8992		0.9983		0.8901	

*** indicates significance at the 1 percent level.
** indicates significance at the 5 percent level.
* indicates significance at the 10 percent level.

The *Context* coefficient is positive in the three models, increasing in statistical significance as the expected value of the gamble increases. This suggests a preference for gambles framed as investment decisions, particularly as the probability of gain increases.

[9] We report the results of a fixed-effects model for the gain domain gambles with an expected value of $5 in the appendix. The *p*-value of the Hausman statistic is marginally significant for the associated RE model.

[10] The number of usable observations. Observations are considered unusable (dropped from the analysis) if the subject did not choose a certainty equivalent or provided multiple equivalents for a gamble. The maximum possible number of observations for the models with expected values of +/-$5 and +/-$45 is 1,192 (149 subjects * 8 gambles) and for expected values of +/-$25 the maximum number is 596 (149 subjects * 4 gambles).

The size (indicated by *Range*) and location (indicated by *Probability*, *Payoff*, and *Both*) of ambiguity play an interesting role in the valuations. Generally, the range of ambiguity does not significantly alter the valuations. It is statistically significant only for gambles with an expected value of $25.

The location of the ambiguity plays a greater role in affecting valuations. Ambiguity in the probability of winning plays a significant role in the valuations for low and high probabilities. The negative coefficient values are indicative of ambiguity aversion. The significantly negative coefficients for *Both* indicate aversion to ambiguity when the decision involves ambiguity in both the probability and the payoff for low and high probabilities of winning.

The *Payoff* coefficient is negative for low and high probabilities indicating ambiguity aversion, but this coefficient is only statistically significant for the expected value of $45. The significantly positive *Payoff* coefficient for the mid probability tends to offset the negative *Range* coefficient for these gambles.

These findings lead to a more general result regarding ambiguity in the gain domain: The subjects are not concerned with the size (or *Range*) of ambiguity but rather the location. We posit that the ambiguity in the probability drives the results. Note that for gambles with expected values of $5 and $45, both coefficients involving ambiguity in the probability are significantly negative (*Probability* and *Both*). While the payoff coefficient is significant for the high probability to win gambles, it is of lesser magnitude than the coefficients involving probability.

<u>The loss domain</u>

The significantly negative constants are as expected. The –10.198 value for gambles with expected values of -$5 suggests risk aversion. However, the –41.342 value for high probability of loss gambles suggests risk seeking behavior. [11]

The context coefficient is not significant in any of the models. This suggests that the subjects did not discern a difference between the gambles framed as lotteries for possible losses versus insurance decisions.

The range and location of ambiguity coefficients present a different picture from that of the gain domain. Unlike the gain domain, the *Range* coefficient is significant in all of the models in the loss domain, indicating that the size of the ambiguity plays an important role in decision making regarding possible losses. The subjects are averse to increases in *Range* for low and high probabilities of loss while exhibiting a preference for mid probabilities. The location coefficients are insignificant for the low and mid probability gambles. However, two of the location coefficients, *Probability* and *Payoff*, are marginally significant and positive for high probabilities of loss. These findings support a more nuanced result regarding the size and location of ambiguity for gambles involving possible losses. This is discussed in more detail in the following section. For now, we will generalize by stating that the subjects are more concerned with the size (or *Range*) of the ambiguity rather than with the location, with possible exception to high probabilities of loss.

[11] In addition, a dummy variable indicating if the subject is female was also included in each of the models to check for overall sex differences (not shown). The coefficient was insignificant in all models in both domains. The most significant p-value was 0.22 in the gain domain and 0.14 for the loss domain. Therefore we cannot reject the hypothesis that the coefficient on the dummy variable for female is equal to zero in either domain. Nevertheless, the coefficient was negative in the gain domain and positive in the loss domain.

4.3. Comparison of our Results with other Research

Hogarth and Kunreuther (1989) conduct experiments involving ambiguity in insurance decisions where subjects responded as either firms or consumers. For comparative purposes we will focus on their findings regarding subjects making consumer decisions for insurance. These authors find that subjects are averse to ambiguity for low probabilities of loss but prefer ambiguity for high probabilities of loss. While the summary statistics of a subset of the gambles presented in Table 5 support this finding, the coefficients for *Range* and ambiguity location for the loss domain models in Table 9 provide a more limited support. The *Range* coefficient is of lesser absolute value for high probability of loss gambles compared to the low and mid probabilities. Furthermore, the positive location coefficients are larger for high probabilities of loss. The location values will more than offset the negative *Range* coefficient if the range of ambiguity is sufficiently small. This would support ambiguity preference for high probabilities of loss.

Di Mauro and Maffioletti (1996) present hypotheses related to the models of Einhorn and Hogarth (1985) and Gardenfors and Sahlin (1982). The hypothesis suggested by Einhorn and Hogarth's anchoring adjustment model is that individuals will switch from ambiguity aversion to preferring ambiguity as the probability of loss increases.[12] The accompanying hypothesis for the Gardenfors and Sahlin maximin model is that subjects will be ambiguity averse regardless of the level of probability. Our results can provide support for both hypotheses. According to the loss domain models in Table 9, there is support for the anchoring adjustment model if the *Range* (or size) of the ambiguity is sufficiently small. However, if the *Range* is large then this will dwarf the location effects for high probability of loss gambles and this supports the maximin model.

[12] This hypothesis is supported by the findings regarding consumer decisions by Hogarth and Kunreuther (1989).

Camerer and Kunreuther (1989) conduct experiments for insurance protection using double-oral auction markets. In these experiments the probabilities of loss are no greater than 50 percent, with the majority being 20 or 30 percent. They introduce ambiguity in the probability of loss through the use of a discrete uniform distribution. The expected values of the probabilities of loss when the consumers are facing ambiguity are 10 and 30 percent. In their example, for a 20 percent loss the range of possible loss probabilities is from 0 to 40 percent. These authors find an insignificant price effect (or willingness-to-pay) with consumer-only ambiguity. We have two instances of ambiguity in the probability with an expected value of 10 percent. We find a significant price difference between the willingness-to-pay to avoid the precise (known) and ambiguous (unknowable) gambles with ranges of 5-15 percent and 0-20 percent chance of loss. [13] The negative and highly significant *Range* coefficient for an expected loss of $5 also suggests ambiguity aversion.

Mangelsdorff and Weber (1994) find, "…a significant difference in attitude towards ambiguity in the gain and in the loss domain." They report significant ambiguity aversion in the gain domain and ambiguity neutrality in the loss domain. We find ambiguity aversion as well in the gain domain, driven by the location of the ambiguity. However, we also find support for ambiguity aversion in the loss domain driven by the size of the ambiguity.

Fox and Tversky (1991) put forth the comparative ignorance hypothesis stating that ambiguity aversion arises from a comparison with less ambiguous events or with more knowledgeable individuals. They find support for this hypothesis through a series of experiments involving bets with ambiguity in the probabilities in the gain domain. Our design eliminates informational asymmetries to avoid this effect regarding more "knowledgeable individuals", i.e. the experimenters. However, our experiment uses a within-subject design where the subjects

[13] Means testing indicates significant differences between these gambles as shown in Table 5.

make decisions regarding both precise and ambiguous gambles. This allows for comparisons between the types of "events", i.e. the gambles. Our results can be interpreted as support for the comparative ignorance hypothesis given the statistically significant differences in valuations between the precise and ambiguous gambles. In the gain domain, subjects exhibit a preference for the precise rather than ambiguous gambles as indicated by the greater certainty equivalents.[14] We find limited support for this claim in the loss domain. The subjects prefer the precise gamble to ambiguity for low probabilities while this is true for high probabilities of loss only if the size of the ambiguity is sufficiently large.

Chow and Sarin (2001) investigate attitudes toward ambiguity in probabilities using bets in the gain domain to investigate the comparative ignorance hypothesis. They find that ambiguity aversion exists in both comparative and non-comparative contexts. In Chow and Sarin (2002), the authors are interested in attitudes to known, unknown, and unknowable uncertainty. They again find evidence of aversion to ambiguity in the probabilities of gambles in the gain domain. Our results also indicate ambiguity aversion regarding probabilities in the gain domain.

The majority of research efforts involving attitudes toward ambiguity involves introducing vagueness in the probability of an event occurring. There is a paucity of results involving ambiguity in the payoff or amount of loss. Furthermore, little has been done involving gambles that jointly involve ambiguity in the probability and payoff combined. We found there to be evidence that the location of ambiguity is a factor in attitudes toward uncertainty. This is particularly the case in the gain domain. However, we recognize that the effect is strongest when the ambiguity is located in the probability for these gambles. In the loss domain, there is evidence of ambiguity aversion driven by the range, or size, of the ambiguity. This aversion increases as the range increases.

[14] This is also evident from the negative location coefficients in the gain domain models in Table 9.

5. Summary and discussion

We have attempted to investigate possible differences in behavior with regard to precise (known) and ambiguous (unknowable) gambles. We conducted an experiment using a new instrument designed to elicit responses in these types of situations. Furthermore, we included ambiguity in each aspect of the gamble: the probability, the outcome, and in both the probability and the outcome simultaneously. This experiment was designed so that the level of information of the subject is equal to that of the experimenters. This was done to minimize any comparative ignorance effects due to a “stacked deck” scenario. In other words, we attempt to ensure that the subjects did not feel that it was possible for the experiment to be rigged by the experimenter.

The subjects exhibit ambiguity aversion in both domains. We found some rather interesting results regarding the ‘location’ of the ambiguity. In the gain domain, subjects exhibit greater ambiguity aversion if the ambiguity is in the probability of the event occurring and also in the case where there is ambiguity in both the probability of the outcome and the amount of the outcome. However, in the loss domain ambiguity aversion is driven primarily by the size of the ambiguity rather than the location. This finding is of note because it may help in determining why consumers pay, in some cases, rather large premiums for insurance. For example, service contracts and extended warranty purchases are significant for electronic devices and automobiles and are quite profitable for providers. In these cases the probability of breakdown is relatively small, yet consumers may feel that the range of repair costs can be considerable. While the expected loss is relatively low, buyers are willing to pay a premium to avoid the uncertainty in the size or amount of possible losses. We also found that there were treatment effects in the gain domain. The subjects exhibited a preference for gambles framed as investment opportunities, as opposed to lotteries. There were no significant treatment effects in the loss domain.

Additional research is necessary to further clarify the role ambiguity plays in decision making. While we have attempted to minimize comparative ignorance effects due to informational asymmetries, a useful future research endeavor would be to use this instrument in a noncomparative framework. Such a project, using a between-subject design, would provide a robust test of the comparative ignorance hypothesis using known and unknowable uncertainty in the vein of Chow and Sarin (2002). Additional research into the location of ambiguity would also be useful in explaining decision-making under uncertainty. This may include an investigation into "thresholds" regarding ambiguity in the outcome. In other words, determining the manner in which the range of ambiguity in the outcome affects valuations. Finally, the development of an experimental technique that involves time lags between the decision and the determination of the outcome would be interesting. Many real-world decisions, such as an insurance purchase, involve making a purchase today as a guard against future possible losses. Incorporating a lag into an experimental setting may be used to measure attitudes toward ambiguity, and discounting, in a more realistic sense.

Appendix

Tables of average valuations.

GAIN DOMAIN								
		Pooled Data			Abstract treatment		Context treatment	
Prob.	Payment	Mean	Std. Dev.	# obs.	Mean	# obs.	Mean	# obs.
10	50	10.19	5.32	145	9.60	72	10.78	73
5-15	50	9.42	4.95	146	9.32	72	9.53	74
0-20	50	8.42	4.87	144	8.91	73	7.91	71
10	45-55	9.79	4.74	143	9.84	70	9.74	73
10	40-60	10.12	5.55	146	9.81	72	10.43	74
5-15	45-55	9.21	5.09	145	8.89	72	9.53	73
10	0-100	10.16	5.39	82	9.54	43	10.85	39
10	25-75	9.19	4.47	83	9.55	44	8.80	39
50	50	24.11	4.92	145	23.64	72	24.58	73
45-55	50	23.94	5.28	143	22.76	71	25.11	72
50	45-55	24.14	5.26	147	23.45	73	24.82	74
45-55	45-55	23.01	4.82	145	22.73	71	23.28	74
90	50	41.56	5.82	147	40.91	73	42.22	74
85-95	50	39.54	5.82	142	38.48	69	40.55	73
80-100	50	40.75	5.9	145	39.88	72	41.61	73
90	45-55	40.98	5.49	147	39.92	73	42.03	74
90	40-60	40.53	5.4	145	39.17	72	41.88	73
85-95	45-55	40.16	5.29	147	39.22	72	41.07	75
90	47-53	40.56	5.69	84	40.96	44	40.12	40
90	44-56	40.31	5.18	84	40.19	44	40.45	40

LOSS DOMAIN								
		Pooled Data			Abstract treatment		Context treatment	
Prob.	Payment	Mean	Std. Dev.	# obs.	Mean	# obs	Mean	#obs
10	50	-9.55	5.91	143	-10.35	71	-8.75	72
5-15	50	-9.99	5.69	146	-10.68	73	-9.30	73
0-20	50	-10.69	5.67	144	-11.45	72	-9.93	72
10	45-55	-9.51	5.87	145	-10.05	73	-8.95	72
10	40-60	-9.74	6.03	144	-10.58	72	-8.90	72
5-15	45-55	-10.17	5.77	144	-10.63	72	-9.71	72
10	47-53	-9.43	5.7	81	-10.50	44	-8.16	37
10	44-56	-10.01	5.77	84	-10.48	44	-9.50	40
50	50	-26.52	5.11	141	-27.01	72	-26.00	69
45-55	50	-25.95	5.03	139	-26.22	68	-25.69	71
50	45-55	-25.94	5.12	143	-26.56	71	-25.33	72
45-55	45-55	-25.46	5.26	140	-25.62	71	-25.29	69
90	50	-41.26	4.57	145	-41.11	71	-41.39	74
85-95	50	-41.14	4.5	143	-41.16	72	-41.13	71
80-100	50	-40.47	4.4	146	-40.25	72	-40.68	74
90	45-55	-41.05	4.83	142	-40.88	72	-41.23	70
90	40-60	-40.6	5.6	144	-41.20	73	-39.99	71
85-95	45-55	-40.85	4.79	143	-41.45	73	-40.21	70
90	0-100	-42.37	6.49	79	-41.93	41	-42.84	38
90	25-75	-41.32	5.36	82	-41.81	43	-40.77	39

Fixed-effects model for gains with expected value of $5

Expected Value	5	
Constant	10.070	***
	(0.257)	
Range	0.003	
	(0.039)	
Probability	-1.245	***
	(0.428)	
Payoff	-0.115	
	(0.327)	
Both	-0.960	**
	(0.432)	
within	0.0324	
between	0.0199	
overall	0.0083	
No. of observations	1034	

*** indicates significance at the 1 percent level.
** indicates significance at the 5 percent level.
* indicates significance at the 1 percent level.

Instructions

Do not communicate with any other participant during this experiment. Participants who do not abide by this rule will be excluded from the experiment and from all payments. If you have questions concerning the experiment please ask me.

In your folders are decision sheets with a list of various choice situations. These situations are of two different types: investment decisions and insurance decisions. An explanation of each type of situation and how the outcomes of these situations are determined will be given to you before you make any decisions.

Insurance Decisions
You have recently purchased a new car or truck. This vehicle may suffer some type of mechanical failure or breakdown and need to be repaired. There are decision sheets in your folder with a list of various choice situations. For each decision, you will choose between taking a chance on the vehicle breaking down and paying the cost of repair or purchasing insurance to insure yourself against having to pay for a repair. There is either a specified percentage chance or a range of percentage chances that the vehicle will need a repair. For example, there might be a 75% chance of a repair or a range such as 25-35%. Also, the cost of a repair is either a specified amount or a range. For example, there might be a $40 repair or a $50-60 repair. You will pay for any repair or insurance purchase with the $60 you earned for completing the survey.

How does the insurance decision work?

Two examples of some possible decisions are shown below.

Example 1.

	Option A	Option B	Your Choice A or B
Decision 1	50% chance at $30 repair	Pay $20.00	

Let's look at Decision 1. You can risk having to pay for a $30 repair with a 50% chance OR you can pay $20 to insure against any repair costs. If you choose to purchase insurance for $20, picking Option B, you will pay this amount and keep the rest of your money. That would be $40 in this case ($60 - $20 insurance = $40). If this decision is chosen for payment and you picked Option A then you will keep the $60 if the vehicle does not breakdown.

Example 2.

	Option A	Option B	Your Choice A or B
Decision 2	5-15% chance at $45-55 repair	Pay $1.00	

Let's look at Decision 2. You can risk having to pay for a $45-55 repair with a 5-15% chance OR you can pay $1 to insure against any repair costs. If you choose to purchase insurance for $1, picking Option B, you will pay this amount and keep the rest of your money. That would be $59 in this case ($60 - $1 insurance = $59). If this decision is chosen for payment and you picked Option A then you will keep the $60 if the vehicle does not breakdown.

How does this loss occur? First, we determine the exact percentage chance of the vehicle needing repair and the exact cost of the repair. In Example 1 these are already determined: the percentage chance of the vehicle needing a repair is 50% and the cost of the repair is $30.

In Example 2, we have to determine the exact percentage chance out of the 5-15% range. Each of the percentage chances of the vehicle needing a repair in the range is equally likely. You will draw a chip from a box of 11 white chips to determine the exact percentage chance of the vehicle needing repair. (There are 11 numbers in the range of 5-15% ⇒ 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15.) Let's suppose you draw a 9. Then the percentage chance of the vehicle needing repair is 9%. Similarly, you will draw a chip from a box of 11 red chips to determine the cost of the repair. (There are 11 numbers in the range of $45-55 ⇒ 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55.) Each of the repair costs is equally likely. Let's suppose you draw a 53. Then the repair cost is $53.

Second, you will roll two ten-sided dice. (One die has "10s", and the other has "1s" on it. If you roll 00 on one die and 0 on the other, then that is rolling 100). Thus the roll will be a number between 1 and 100. If the number you roll is equal to or smaller than the percentage chance of the vehicle needing a repair, then your vehicle has had a breakdown and you will have to pay for repairs. If the number is higher than the percentage chance of the vehicle needing a repair, you do not have to pay any repair costs.

Continuing with Example 2. Suppose you have chosen to take a chance on the vehicle needing a repair and have drawn chips to determine there is a 9% chance of a repair costing $53. Then if you roll a number between 1 and 9, the vehicle needs a repair and you must pay the repair cost of $53. If you roll a number between 10 and 100, the vehicle does not need any repairs. Now suppose that, instead of taking a chance on the vehicle needing a repair, you chose to pay $1 in Decision 2 of Example 2. Then you will keep $59 ($60 - $1 = $59).

At the end of all of the sessions today, one of your insurance decisions from a decision sheet will be chosen randomly, and you will either take a chance on paying for a repair or pay for insurance. Your best strategy is to treat each decision as if it could be the one you will pay for.

I will now show you how these experiments are conducted.

Now is the time for questions. Feel free to ask any questions that you may have.

All of the participants have received identical decision sheets in the experiment. Please fill out the decision sheets in the order you find them. Remember to put your ID Code on each sheet. After you have completed each sheet please place it immediately in the yellow folder. You are not allowed to view or correct any decision sheets that you have placed in the yellow folder.

Investment Decisions

In this experiment, you are given an opportunity to invest between two different firms, Firm A and Firm B. There are decision sheets in your folder with lists of different decisions. For each decision, you will choose between investing in Firm A which is a risky investment with a larger possible return or investing in Firm B which has a certain return. For Firm A, there is either a specified percentage chance or a range of percentage chances that the firm will be successful. For example, there might be a 75% chance of a return or a range such as 25-35%. Also, the investment return for Firm A is either a specified amount or a range. For example, there might be a $40 return or a $50-60 return on investing.

How does investing work?

Two examples of some possible decisions are shown below.

Example 1.

	Firm A	Firm B	Your Choice A or B
Decision 1	10% chance at $20	$1.00	

Let's look at Decision 1. You can choose to invest in Firm A with a 10% chance at a $20 return OR you can choose to invest in Firm B and receive a certain return of $1.00. If this decision is chosen for payment and you picked Firm A then you will receive $20 if the firm is successful. If you picked Firm B you will receive $1.

Example 2.

	Firm A	Firm B	Your Choice A or B
Decision 2	85-95% chance at $45-55	$31.00	

Let's look at Decision 2 in this example. You can choose to invest in Firm A with an 85-95% chance at a $45-55 return OR you can choose to invest in Firm B and receive a certain return of $31.00. If this decision is chosen for payment and you picked Firm A then you will receive $45-55 if the firm is successful. If you picked Firm B you will receive $31.

How does this investment work? First, we have to determine the exact percentage chance of a return on investment and the exact amount of the return for Firm A. In Example 1 these are already determined: the percentage chance of a return is 10% and the return is $20.

In Example 2, we have to determine the exact percentage chance of a return out of the 85-95% range. Each of the percentage chances of a return in the range is equally likely. You will draw a chip from a box of 11 white chips to determine the exact percentage chance of a return. (There are 11 numbers in the range of 85-95% ⇒ 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95.) Let's suppose you draw a 92. Then the percentage chance of a return is 92%. Similarly, you will draw a chip from a box of 11 red chips to determine the amount of the return on your investment. (There are 11 numbers in the range of $45-55 ⇒ 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55.) Let's suppose you draw a 48. Then the return is $48 if the firm is successful.

Second, you will roll two ten-sided dice to see if the firm is successful. (One die has "10s", and the other has "1s" on it. If you roll 00 on one die and 0 on the other, then that is rolling 100). Thus the roll will be a number between 1 and 100. If the number you roll is equal to or smaller than the percentage chance of a return, the firm is successful and you will ***receive*** the investment return. If the number is higher than the percentage chance of a return, the firm is not successful and you will ***not*** receive any return on your investment.

Continuing with Example 2. Suppose you have chosen to invest in Firm A and the chips have been drawn to determine there is a 92% chance of a return of $48. Then if you roll a number between 1 and 92, the firm is successful and you receive the $48 return. If you roll a number between 93 and 100, the firm is unsuccessful and you do not receive any return on your investment.

At the end of all of the sessions today, one of your investment decisions from a decision sheet will be chosen randomly, and you will be paid in cash for your decision about this investment opportunity. Your best strategy is to treat each decision as if it could be the one you get paid for.

I will now show you how these experiments are conducted.

Now is the time for questions. Feel free to ask any questions that you may have.

All of the participants have received identical decision sheets in the experiment. Please fill out the decision sheets in the order you find them. Remember to put your ID Code on each sheet. After you have completed each sheet please place it immediately in the blue folder. You are not allowed to view or correct any decision sheets that you have placed in the blue folder.

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