THE EFFECTS OF CONTROL ON DECISION MAKING FROM A PROSPECT THEORY FRAMEWORK

by

DIANA L. YOUNG

(Under the Direction of Adam S. Goodie)

ABSTRACT

Most decision making research investigates risk taking behavior involving the outcome of random events; however, most everyday decisions involve some amount of personal control (e.g. skill or knowledge) in the outcome of events. Two experiments investigated differences in decision making behavior between two distinct types of wagers: wagering on the outcome of random events and wagering on the outcome of events that are characterized by control. Experiment 1 offered participants bets based on the correctness of their answers to general knowledge questions, and Experiment 2 offered participants bets based on their ability to successfully putt a golf ball. Responses for these wagers were modeled in a prospect theory framework to posit psychological mechanisms behind decision making behavior. Both experiments found that participants betting on tasks characterized by control weighted probabilities more prescriptively than participants betting on chance events. Implications for applied and natural decisions are discussed, and plans for future research are hypothesized.

Index words: decision making, prospect theory, control, knowledge, skill, probability, choice, gambling

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DIANA L. YOUNG

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DIANA L. YOUNG

Major Professor:	Adam S. Goodie
Committee:	Richard L. Marsh Robert P. Mahan

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
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CHAPTER 1

INTRODUCTION

The majority of decision making research focuses on risky prospects or gambles in which the outcomes of those prospects are completely dependent upon chance events (for a review see Starmer, 2000). However, decisions that people make in the naturalistic environment generally involve some amount of personal control in the outcomes with unknown probabilities of occurrence (e.g., driving a car, playing the stock market, choosing auto insurance carrier). If everyday decisions frequently involve events or outcomes that are dependent upon tasks that the decision maker can control, it follows that research should also attempt to examine decision making behavior by assessing wagers in the control domain rather than simply in the chance domain. The present study investigated the changes in decision making behavior due to the inclusion or exclusion of a control component in the prospects being evaluated.

What is Control?

The term control is utilized in a variety of ways in psychology literature to characterize human behavior. In fact, there is much debate over any single definition or construct for control (for a review see Skinner, 1996). Nevertheless, many researchers' definitions of control share the common characteristic of a direct, causal relationship between a person's behavior and an event outcome. Langer (1975) stated that successful skilled tasks are controllable because there is a causal link between one's behavior and a desirable event outcome. Miller (1979) coined the term "instrumental control" to refer to the ability of a person to make a response that modifies an aversive event. Similarly, health psychology literature regularly utilizes Thompson's (1981) control hypothesis, which defines control as "the belief that one has at one's disposal a response that can influence the aversiveness of an event" (p. 89). More recently, Burger (1989) defined control from a social psychology perspective as "the perceived ability to significantly alter events" (p. 246). Rodin (1990) defined objective control as the ability to influence outcomes through selective responding.

The definition of control that represents the fundamental attributes of the present study characterizes control as "probability alterability" (Goodie, 2003). Goodie posits that if participants can take steps to positively alter the success rate of a given task, then that task is characterized by control. He uses the example of playing roulette versus answering questions on a knowledge-based test to better explain this definition. In the game of roulette, there are no steps that one can take to increase the odds of a win in successive plays. Each play in roulette is completely dependent upon chance events, thus there is no way for a person to positively affect the outcome. On the other hand, because one can take active steps to increase the odds of a earning a better score on a general knowledge test by studying certain knowledge topics (history, math, etc.), taking that test is a task that is characterized by control.

This study uses Goodie's (2003) definition of control over other definitions for a variety of reasons. The current study offered wagers to participants based on positive outcomes. Miller's (1979) and Thompson's (1981) conceptions of control, whose definitions focus on the avoidance of negative outcomes, are not appropriate. Langer's (1975) definition of control requires that, for a task to be controllable, the actor must be skilled in the task at hand; Goodie's (2003) definition of control does not require that the actor be skilled in the task. Burger's (1989) definition of control requires that the decision maker believe he can significantly alter events, which calls into question how much influence qualifies as “significant.” Finally, Rodin’s conception of control relies on a purely behavioral definition – selective responding – to define objective control; however, Goodie’s (2003) definition of control is not limited to tasks that involve only selective responding.

Many studies have examined the ways in which perceived control impacts one’s decision making behavior. Langer (1975) found that participants accepted bets more often and expressed more confidence in chance bets when the façade of a skill element was added to the situation, thus inducing an illusion of control. In another study, when participants imagined they were given a week to practice a completely chance-determined gambling task, the participants believed they could improve their performance in that task, thus revealing an illusion of control (Dykstra & Dollinger, 1990). Chau and Phillips (1995) altered participants’ control over tasks to make the outcomes of the tasks seem either task-relevant or task-irrelevant; the researchers found that the skill-relevant manipulation made participants bet more, unlike the skill-irrelevant manipulation. In two other studies, participants favored betting on questions about subject matter in which they felt competent rather than on random chance events (Heath & Tversky, 1991; Taylor, 1995). People are more overconfident when answering questions about past events, which can be studied, than about future event questions, which cannot be studied (Wright, 1982). In a gambling task study that involved deciding whether to have a third-party surgeon perform a safe or risky operation, participants accepted more risk when the risky option was based on an element of control (the surgeon’s skill) rather than on pure chance (Brandstatter & Schwarzenberger, 2001). These results lend weight to the notion that people assess risk (and subsequently behave) differently if perceived control plays a role in the outcome of the event in question.

Previous decision making research in the Georgia Decision Lab has focused on Goodie's (2003) Georgia Gambling Task (GGT). The GGT is an individual choice task used to measure confidence, accuracy, overconfidence, and risk taking in gambling situations. The task elicited acceptance or rejection of bets on the basis of answers to general knowledge questions. The GGT has been utilized in various studies (Goodie, 2003; Campbell, Goodie, & Foster, 2004; Goodie & Young, 2007) to gain a broad estimate of risk taking in terms of bet acceptance.

The present study is an extension of Goodie (2003) in two distinct ways. First, the present study utilized a betting structure in which certainty equivalents for bets were elicited from participants to model overall decision making behavior from a prospect theory framework (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Modeling decision making behavior from a prospect theory framework allows for a direct examination of changes in the value and weighting of prospects, providing a more sophisticated method of measuring decision making behavior than as used in the original form of the GGT. Modeling via prospect theory also easily incorporates monetary gambles, as utilized in the present experiments. Second, whereas Goodie (2003) offered bets based solely on one's success in knowledge-based tasks, this study examined an additional task characterized by control: skill-based tasks. Skill-based tasks can be characterized by control because a skilled task can be practiced; therefore, the probability of success in future administrations of that task can be positively altered. By examining both knowledge-based and skill-based tasks, this study added to the ecological validity of how the perception of control in the outcome of an event affects decision making behavior. Here, two experiments assessed decision making behavior for monetary gambles based on either control in the outcome of events or purely random events.

On Comparing Uncertain Outcomes to Objective Probabilities

This study directly compares bets with objective probabilities to bets with uncertain (ambiguous) outcomes. The terms ambiguity and uncertainty are used interchangeably in decision making literature to describe outcomes whose probabilities are not known. When encountering uncertainty in a prospect, decision makers must rely on likelihoods to assess subjective probability estimates of the outcomes. In the past it has been argued that one cannot directly compare decisions under risk with decisions under uncertainty, or that decision makers are less sensitive to uncertainty than to risk (Tversky & Wakker, 1995).

Recently, however, researchers have made an argument for the efficacy of modeling and decomposing decision behavior in the domain of uncertainty as well as the domain of risk (Fox & Tversky, 1998; Kilka & Weber, 2001; Wu & Gonzalez, 1996; Wakker, 2004). Fox and Tversky's (1998) two-stage model of decision making under uncertainty argues that beliefs about the uncertain probability success of events can be transformed onto the risky weighting function that is used for objective probabilities. The present study relates decisions under uncertainty with decisions under risk by asking participants to estimate one's confidence in the success of skill-based and knowledge-based tasks. In the case of a participant making decisions on a golf putt, for instance, the decision maker first assesses how confident he is in sinking a golf putt, and then he transforms this confidence using his normal risky weighting function into a subjective probability.

CHAPTER 2

GENERAL METHOD AND RESULTS

Two experiments utilized a two-group experimental design involving a two-outcome gambling decision task, with all participants randomly assigned to either the “Random” group or the “Control” group. Random group participants encountered bets based on random chance events (a gamble that offered an XX% probability for a win). Control group participants encountered bets based on their success in answering general knowledge questions (Experiment 1) or in putting a golf ball (Experiment 2).

It is important to clarify the preference for labeling one group as the “Control” group. Generally, experiments utilize the term “control” to characterize the non-manipulation condition in an experimental-control study. However, given the current study’s unique effort to examine the effects of control in the outcome of various types of events on behavior, it is appropriate to label those in the manipulation condition as members of the “Control” group.

As in the original form of the GGT (Goodie, 2003), both experiments offered participants bet scenarios based on seven probabilities for a winning outcome (.51, .55, .65, .75, .85, .95, and .99; adapted from Goodie, 2003). This study modeled fifteen bet outcome win-and-loss (w-l) amounts and betting procedures after Gonzalez and Wu (1999). Table 1 presents the 105 bets offered to participants in both experiments based on crossing probabilities with w-l amounts. A Gains-Only betting structure was used (Goodie & Young, 2007), with all loss amounts for offered bets equal to or greater than $0.

All participants considered a) a two-option bet with a specific probability of a win and specific w-l amounts and b) various sure thing alternatives related to that bet; participants then estimated certainty equivalents for each bet. A certainty equivalent (CE) is defined in this study as an amount of money that the participant views as equivalent in subjective value to the bet scenario being offered (Tversky & Kahneman, 1992; Gonzalez & Wu, 1999). For example, a person may value a .51 probability of gaining $100 and a .49 probability of gaining $0 as subjectively worth $37. In this instance, the CE for ($100, .51; $0, .49) is $37.

Modeling the data

The current study utilizes a prospect theory framework (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) to model descriptive decision making behavior. Prospect theory (PT) is an individual choice model that assesses various patterns of risk and examines decision behavior when there are a small number of outcomes to choose from. PT takes into account the subjective utility attributed to a given change in wealth (a value function) and the subjective weight that is attached to the probability of a possible event outcome (a weighting function). In the current study's context, the value of a CE can be modeled according to both the utility of the prospects' outcomes and the weighting of the prospects' probabilities. The basic mathematical formulation of this concept is:

$$v(CE) = w(p)v(X) + \{1 - w(p)\}v(Y), \qquad (1)$$

where v(.) is a value function and w(.) is a probability weighting function, with p representing the probability of a win, and X and Y equaling money won and lost in the different outcomes of a two-option bet, respectively.

The generally accepted value function (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) takes the form:

$$v(X) = \theta X^{\alpha}.$$

In the value function, θ is a scaling parameter of limited theoretical interest. The α parameter describes the degree of curvature in the value function; α psychologically represents the degree to which the value of a gain or loss in wealth changes as a function of the magnitude of the change in wealth. Figure 1(a) presents a typical value function with respect to gains in wealth.

The form of PT's probability weighting function is generally accepted as being a regressive, inverse-S shape curve, with people overweighting small probabilities and underweighting medium and large probabilities. Figure 1b presents the weighting function. The current study employed a mathematical formulation of the weighting function conceived by Gonzalez and Wu (1999) which allows for psychological interpretations of both an outcome's discriminability and attractiveness to an individual. Discriminability refers to sensitivity to the differences among various probabilities between 0 and 1 and is indexed by the curvature of the weighting function. Generally, there is very sensitive discrimination of changes in probability near the endpoints (close to impossibility and certainty) but diminished sensitivity to changes in the middle of the probability scale. A weighting function that hugs the identity line closely would indicate a relatively rational weighting of probabilities, whereas the opposite would be true of a weighting function that is more curvilinear. Attractiveness, on the other hand, refers to the amount of overall overweighting or underweighting of probabilities and is indexed by the elevation of the weighting function. A weighting function that indicates a large amount of attractiveness among prospects would have a curve that is above one with a small amount of attractiveness. The weighting function proposed by Gonzalez and Wu is as follows:

$$w(p) = (\delta p^{\gamma})/\{\delta p^{\gamma}+(1-p)^{\gamma}\}. \quad (2)$$

Here, γ represents discriminability (the curvature parameter) and δ represents attractiveness (the elevation parameter). The weighting function can be simplified to the following equation, with *O* representing the odds of winning:

$$w(p) = \{1 + (\delta O^{\gamma})^{-1}\}^{-1}, \quad O = p/(1-p). \quad (3)$$

After substituting and simplifying the value function parameters in the initial PT equation, the following function is produced:

$$\text{CE}^{\alpha} = w(p)\,(X^{\alpha} - Y^{\alpha}) + Y^{\alpha}. \quad (4)$$

Solving Equation 4 for CE,

$$\log(\text{CE}) = \alpha^{-1} \log\{w(p)\,(X^{\alpha} - Y^{\alpha}) + Y^{\alpha}\}. \quad (5)$$

The final step is the substitution of the weighting function into the model. The model, after substituting all appropriate forms, is the following:

$$\log(\text{CE})_{ij} = \alpha_i^{-1} \log[\{1+ (\delta_i O_{ij}^{\gamma_i})^{-1}\}^{-1} (X_{ij}^{\alpha_I} - Y_{ij}^{\alpha_i}) + Y_{ij}^{\alpha_i}] + e_{ij}, \quad (6)$$

with *i* indexing subjects and *j* indexing repeated measures on subjects. This is a nonlinear mixed model to account for parameters that vary across individuals. Included in this equation are

$$\alpha_i = \alpha_o + a_i,$$

$$\gamma_i = \gamma_o + c_i, \text{ and}$$

$$\delta_i = \delta_o + d_i,.$$

In these forms, α_o, γ_o, and δ_o are population level values of the weighting and value functions' parameters, and a_i, c_i, and d_i, represent subject-specific random effects that account for individual differences in each parameter. This model is fitted to each participant's set of CE responses to obtain value and weighting function curves and calculate individual- and group-level parameter estimates.

The hypothesis of the present study is that control in the outcome of a task affects one's decision making behavior. Goodie (2003; Goodie & Young, 2007) asserts that there is a systematic difference in risk-taking strategy between betting on the correctness of a general knowledge question with a given subjective probability of success and betting on a random event's occurrence with the same objective probability of success. The current study directly examines Goodie's assertion by measuring differences in CE values across a spectrum of bet scenarios and two dimensions of control: knowledge and skill. Here, participants encounter bets based on the confidence they have in their answers to general knowledge questions or their skill in putting. Do people bet differently on random events than they do on event outcomes that are characterized by control? If so, one can infer that the element of control alters a person's estimation of risk. If not, implying that there is no difference in CE value between bets based on random events versus bets based on knowledge or skill, then perhaps personal control has no effect on decision making behavior or one's assessment of risk.

Modeling each participant's data to this study's conception of the PT model allows for an efficient way of examining differences in overall patterns of risk taking between groups. Changes in the curvature of the value function between groups would indicate a difference in the way gains in wealth are valued as a result of control in the outcome of events. For instance, a group with an α value that is significantly smaller than the other group's would suggest that there is greater diminished sensitivity to gains for that group. A significant difference in the curvature of the weighting function between groups would indicate a more or less linear weighting function, thus a more or less normative weighting of probabilities. This would suggest that the group with a γ closer to 1.0 would have a more normative (rational) weighting of probabilities. Differences in the elevation of the weighting function between groups would suggest an overall increase or decrease in the attractiveness of outcomes, irrespective of outcome probability, which would intimate an increase or decrease in one's overall assessment of risk.

Participants in both experiments were recruited from the Research Pool of the Psychology Department at the University of Georgia and compensated with partial credit toward lower-division psychology courses. Experimenters gave all participants the opportunity to play out one of their bets for real money at the end of their experiment session (1/5 of the total amount of the bet played), adding ecological validity to the study. Participants who had already participated in related experiments could not participate.

Experiment 1

Participants were randomly assigned to either the Random group (betting on random events) or the Control group (betting on knowledge). Random group participants encountered bets based on the outcome of a lottery game. Control group participants encountered bets based on the correctness of their answers to general knowledge questions concerning US state populations, which is an extension of Goodie (2003) and Goodie and Young (2007). Participants bet on their knowledge (or on random events) in two phases, which incorporated three question-types.

Phase 1. General knowledge and assessment of confidence. During Phase 1 of the experiment, both groups answered the same two types of questions. The first question type asked participants for answers to 100 general knowledge questions (GKQ) in a two-alternative forced choice format. This question type selected two U.S. states at random and asked for a binary comparison of state population. After participants answered a GKQ, they assessed their confidence in that chosen answer, based on one of the following seven categories: 51%, 55%, 65%, 75%, 85%, 95%, and 99%. This question type was adopted and altered from that used by Goodie (2003; Campbell, Goodie, & Foster, 2004). After participants answered and assessed their confidence in all 100 GKQs, they then chose a GKQ they felt best exemplified each of the seven confidence categories (51%, 55%, etc.). Although this information was only necessary for the Control group, participants in both groups completed Phase 1 to avoid any possible confounding variables.

Phase 2. Betting on answers. The third question type elicited CE estimates for 105 bets (refer to Table 1 for the 105 bets offered).

Participants considered one bet at a time; each bet scenario revealed the amount of money gained for a win, the amount of money gained for a loss, and the parameters of the bet (i.e., a .75 probability of a win or a GKQ answer that the participant felt 75% confident in). The computer then offered various CEs for the bet of interest, listing them in descending order from the amount gained if the bet was won to the amount gained if the bet was lost with equal spacing between intervals.

Method

Participants and materials. Forty-nine participants (Random = 27) took part in Experiment 1. The computerized portions of the study, which included all recorded responses, were presented on a personal computer using software developed in the Delphi ™ environment. Experimenters ran up to three participants at a time in a room containing three separate computer stations.

Procedure. Both Random and Control participants completed Phase 1. Following instructions in which they learned that one of the following bets would be played out for real money, participants in both groups also completed Phase 2.

Random participants encountered a bet scenario at the top of the computer screen, displaying the probability of a win, the amount of money gained if the outcome was a win, and the amount of money (if any) gained if the outcome was a loss. Control participants encountered one of the seven prototypical GKQs at the top of the computer screen, with their answer indicated and w-l amounts displayed. A bet outcome resulted in a "win" if the participant correctly answered the GKQ and a "loss" if the participant incorrectly answered the GKQ (see Figures 2a and 2b for examples of Phase 2 displays for both Random and Control bets, respectively).

Participants in both groups responded to bets in Phase 2 by selecting the smallest sure thing amount on the screen that they would be willing to accept in place of the bet being offered. When participants responded, a subsequent screen provided a new, narrower range of sure thing values for the participants to respond to, until a final smallest sure thing was chosen; this process estimated a CE value to the nearest $1.00. This method of estimating CE values prohibited violations of dominance within any given trial and narrowed each participant's CE value for a bet to the nearest dollar. The computerized program recorded all CE responses from participants.

One of the 105 bets was picked at random and played out for money (1/5 face value) after completing Phase 2. Participants filled out demographic questionnaires that ended the experiment session.

Experiment 1 Results and Discussion

Multivariate distances of each subjects' random effect vector from the mean were calculated, and those with the largest squared distances from the mean were removed prior to analysis (three participants total). Various trials (no more than 3 trials per participant) were also omitted from analysis due to data reflecting vastly irregular responses. Preliminary analyses indicate no significant difference in raw CE values between the two groups. Irrespective of bet probability or win-loss amount, the average CE value for Control participants was about $2 lower than that for Random participants, revealing a tendency for Control participants to be less risk-taking than their Random counterparts, although this difference in raw CE value was not significant. Figure 3 shows CE differences across the seven bet probabilities offered to participants. As mentioned previously, however, assessing raw CE observations alone does not offer a complete representation of decision making behavior. This study main goal is to discover more specific patterns of decision making behavior by modeling the data and assessing differences in the value and weighting functions of the PT model, and in particular utilizing Gonzalez and Wu's (1999) psychological interpretations of curvature and elevation.

Results for implementing participants' CE values into the PT framework were computed by fitting participant data to the nonlinear mixed effect model that assessed parameters for both the generally-accepted value function (α) and the Gonzalez and Wu (1999) probability weighting function discussed previously (γ and δ). This model is reformulated below (Eq. 6).

$$\log(CE)_{ij} = \alpha_i^{-1} \log\left[\{1+ (\delta_i O_{ij}^{\gamma_i})^{-1}\}^{-1} (X_{ij}^{\alpha_I} - Y_{ij}^{\alpha_i}) + Y_{ij}^{\alpha_i}\right] + e_{ij}, \quad j = 1,\ldots n.$$

Taking into consideration all bets offered, mean α value differences were not statistically significant between Control participants (mean = 0.910) and Random participants (mean = 0.966); ($F(1,10015) = 0.3017$, $p = .58$). Figure 4 presents the value function curves for both

Random and Control groups for Experiment 1. Mean δ value differences were also not statistically significant (Control = 1.009, Random = 1.397; $F(1,10015) = 1.8430$, $p = .17$). Control participants had significantly higher γ values than did Random participants (Control = 0.774, Random = 0.497; $F(1,10015) = 8.6357$, $p = .003$). Figure 5(a) presents the partial weighting function adopted from Gonzalez and Wu (1999), utilizing γ and δ parameter means from both groups.

The curvature of the value function, represented by α, determines the amount of perceived value of a gain or loss of a given amount of money for participants. Results suggest that there is no overall disparity in the value function's curvature between Control participants and Random participants (Figure 4). It can thus be inferred that the marginal value of gains is not a situationally-dependent construct that fluctuates due to the nature of the task itself. Tasks characterized by control do not appear to have an effect on the subjective utility of gains in wealth.

The lack of significant differences in δ suggests that there may be no overall increased attractiveness in risk taking when betting on knowledge versus random events. Results of past decision making research suggest that a perception of control over an outcome should increase risk-taking across all probabilities (Weinstein, 1980; Langer, 1975; Dixon et al., 1998). Experiment 1 results did not find the same maladaptive risk- taking behavior in participants betting on their answers to general knowledge questions. There remains, for those betting on knowledge, a tendency to overweight small probabilities and underweight medium and large probabilities. One should note, however, given that this is one of the first control-based studies to investigate behavior from a PT framework, it is difficult to directly relate Langer, Dixon, and Weinstein's previous research with this current set of experiments.

As seen in Figure 5a, the curvature of the weighting function for Control participants is more linear than that for Random participants, which is represented by γ values closer to 1.0. There is less overweighting of small probabilities and underweighting of medium and large probabilities when betting on answers to general knowledge questions than when betting on random events such as lotteries. Moreover, participants in the Control group were better able to discriminate between probabilities throughout the study. This indicates a more prescriptive risk attitude for those betting on tasks characterized by control. A more normative weighting of probabilities by those betting on their knowledge would hypothetically maximize participants' overall winnings if given many bets across a full probability scale. Figure 5b represents the hypothetical weighting functions for both Control and Random groups if one extends the estimated γ and δ parameter values across a full probability scale.

Because the nature of this study did not originate from any true assumptions of decision making behavior in the prospect theory context, Experiment 1 could be seen as an exploratory study. In light of this, Experiment 2 has a clearer hypothesis that claims that there should be a more linear weighting of probabilities when betting on tasks that are characterized by control.

Experiment 2

Experiment 2 was conducted in an effort both to replicate the findings of Experiment 1 and to extend the concept of control to a second domain: physical skill. As in Experiment 1, participants in Experiment 2 were randomly assigned to "Random" and "Control" groups. Random participants encountered bets based on random chance events, and Control participants encountered bets based on their skill in successfully sinking a golf putt.

Method

Participants and materials. Forty participants were recruited for Experiment 2. Experimenters ran participants one at a time in a room containing one computer desk, a 12’x4’ elevated golf putting green, and four golf putters (two left-handed and two right-handed putters, each of differing lengths). The computerized portions of the study, which included all recorded responses, were presented on a personal computer using Delphi ™ software.

Procedure. Following instructions in which they learned that one of the following bets would be played out for real money, Random participants encountered 105 computerized bets, one at a time, in a manner similar to that in Phase 2 of Experiment 1.

Control participants began the study by practicing golf putts on the putting green until they felt comfortable with their putting abilities. Participants then placed golf balls on seven distinct places on the green corresponding to the seven probabilities that they would encounter in the betting portion of the study. For example, instructions for placing a golf ball at the 51% confidence spot were as follows:

> *Please place the golf ball at a spot on the green where you are 51% confident you could successfully putt the golf ball into the hole. In other words, find a place on the green where you feel that, if you putt the ball from that specific spot 100 times, you could sink the putt 51 of those 100 times.*

After placing all seven golf balls in their subjective confidence points on the green, Control participants also encountered 105 computerized bets. Unlike the bets encountered by Random participants, the bets offered to the Control participants were based on their success in making their golf putts. See Figures 6a and 6b for a depiction of both computerized betting formats offered.

As in Experiment 1, one of the 105 bets was picked at random and played out for money (1/5 face value) after completing Phase 2. Participants filled out demographic questionnaires that ended the experiment session.

Experiment 2 Results and Discussion

Four participants were removed from analysis by calculating multivariate distances of each subjects' random effects vector from the mean and eliminating largely irregular outliers. Preliminary results indicate higher overall CE values for Control participants than for Random participants. The average overall CE value for Control participants was $7 higher than that for Random participants, indicating that Control participants were slightly more risk-taking than Random participants. Figure 7 shows CE differences across the seven bet probabilities offered to participants for Experiment 2. These raw CE value differences were, as in Experiment 1, not significant at the p=.05 level. Again, because this study's goal is to explain more specific patterns of risk, CE responses were implemented into the prospect theory model.

Results were computed for Experiment 2 by implementing participants' CE values into the PT framework. Taking into consideration all bets offered, mean α value differences were statistically significant between Control participants (mean = 0.782) and Random participants (mean = 0.946), ($F(1, 3734)=5.52$, $p = .02$). The difference in mean γ values (Control = 0.771, Random = 0.529) was statistically significant ($F(1, 3734)=4.36$, $p = .03$). Although the difference in δ between groups was not statistically significant (Control = 0.762, Random = 0.695; $F(1,3734) = 0.130$, $p = .72$), a mixed model ANOVA comparing all three parameters jointly revealed a significant difference ($F(4, 3734)=3.46$, $p = .02$).

Results found significantly lower α values for those betting on their skill rather than for those betting on random events, suggesting that the overall value function for Control participants is more curved than for Random participants (Figure 8). It can thus be inferred that the marginal value of gains generally decreases with magnitude at a more rapid rate for Control participants than for Random participants.

The lack of significant differences in the weighting function's δ parameter suggests that there may be no overall shift in risk taking when betting on skill versus random events, just as in Experiment 1. Again, this appears to run contrary to previous research that proposes an increase in risk-taking behavior for illusion of control studies.

As presented in Figure 9a, the weighting function for Control participants is more linear than that for Random participants, indicating a more prescriptive risk attitude for those betting on their own skill in putting. People overweight small probabilities less and underweight large probabilities less when betting on the success of a golf putt (a task characterized by control) than when betting on random events, giving rise to a weighting function that predicts more rational decision making. People making decisions on their own skill may weight probabilities more normatively than people making decisions on random events, thereby leading to more positive outcomes in the long run.

CHAPTER 3

GENERAL DISCUSSION

The two experiments reported here examined how decision making behavior systematically differs between two types of gambles - random chance gambles versus gambles whose outcomes are characterized by personal control – utilizing the prospect theory framework to evaluate certainty equivalents elicited within the Georgia Gambling Task (Goodie, 2003). It was found that when a gamble's outcome is contingent upon a task that is characterized by personal control, there is less overweighting and underweighting of the odds of outcomes, yielding more prescriptive risk-taking behavior. In Experiment 1, participants betting on their answers to general knowledge question evaluated probabilities more normatively than participants betting on random chance events. This finding was replicated in Experiment 2, in which participants betting on their ability to sink a golf putt also evaluated probabilities more normatively than participants betting on random chance. Results from both of the present experiments reveal that betting on the success of an event that is contingent upon their personal control yields a weighting function that is less regressive, and generally more linear, than betting on an event with the same probability of occurrence that is not contingent upon personal control.

The results of this study suggest that decision making concerning events that are characterized by control is adaptive. As Figures 5b and 9b indicate, one's weighting curve hugs the identity line more when the decision maker is dealing with outcomes that are characterized by control, which clearly indicates that those decisions are generally more rational. The argument that the perception of control is adaptive gains support from a health psychology perspective; it's been found that the perception of control leads to a more healthy, positive outcome within the individual in terms of reducing tension and arousal (Thompson, 1981) and increasing psychological tolerance (Taylor and Brown, 1994). Skinner (1996) speculates that the notion that one has the ability to improve the odds of a positive outcome leads to positive psychological consequences. The present study's results are consistent with those studies, but from a decision making perspective; when one has the ability to improve the odds of a positive outcome, it also leads to more rational decisions.

Other researchers have examined the ways in which the perception of control can be maladaptive. Dixon, et al. (1998) found that people may forfeit money for the opportunity to engage in superstitious activities that give the illusion of control, thereby decreasing their overall winnings. Weinstein (1980) posited that the degree of perceived controllability would influence the amount of optimistic bias evoked by different events. Participants rated their own chances to be above average for positive events and below average for negative events, thus creating a self-serving bias that can lead to either positive or negative outcomes. As this paper argues, however, other studies have measured aspects of decision making from a more limited view (overall winnings, superstitious behaviors, etc.). Modeling the effects of control on decision making via prospect theory, however, allows for a more direct examination of many patterns of risk that Kahneman and Tversky initially intended to investigate.

These results also differ from the results of other studies in the Georgia Decision Lab that investigated the effects of control on decision making. Goodie (2003) initially found that people are more risk-taking with tasks that are characterized by control. However, the present findings appear to be at odds with Goodie's (2003) initial assertion that control may lead to risk taking that is less prescriptive. Likewise, Goodie and Young (2007) found a trend towards risk-taking in the control domain, suggesting a change in attractiveness rather than discrimination. How can the current results contend with Goodie's previous research (2003; Goodie & Young, 2007) that found an increase in risk-taking in the control domain? The methods used to elicit decision making behavior have been improved upon in the current study by utilizing the PT framework. Both Goodie (2003) and Goodie and Young (2007) utilize the original form of the GGT, which does not allow for assessments of subjective weighting of probabilities. The PT framework allows for a comprehensive representation of decision making behavior (for a review of PT, see Edwards, 1996). The results found in this paper can be considered, therefore, more accurate representations of the effects on decision making behavior because the framework used here is more sophisticated.

It had been previously conjectured by some that if CE values were modeled in a PT framework, betting on one's own knowledge would "induce weighting functions that are more progressive," representing an underweighting of low probabilities and an overweighting of high probabilities (Goodie, 2003, p.609). On the other hand, others (Gonzalez & Wu, 1999) have suggested that domains in which the decision maker perceives control in the outcome of events would elicit weighting functions with γ values closer to 1.0, suggesting a more linear weighting of probabilities. Although this study did not find a progressive weighting function as Goodie (2003) suggested, γ values in the control domain did become closer to 1.0, which follows Gonzalez and Wu's hypothetical claim.

Limitations and Future Directions

Because the experimenters in Experiment 2 directly asked Control participants to place a ball at specific confidence points on the putting green, participants may have felt a need to "hedge their bets." For instance, when asked to place the golf ball where they were 99% confident they could make the putt, they may have placed the ball where they were 100% confident instead. Although no participants appeared knowledgeable of the fact that one of their bets may be played out for real money, hedging bets on confidence may have been done in an effort to please the experimenter or not seem foolish in front of an audience. Unfortunately, there is no way to be certain that Control participants were being completely honest in self-reports of confidence.

At the present time, there is no sufficient explanation for the significant difference in the α parameter for Experiment 2. A more curved value function for those betting on knowledge suggests that diminished sensitivity to gains is more pronounced in this condition. However, because the same effect was not found in Experiment 1's Control participants, it is hard to generate a suitable explanation for the findings. A partial-replication study currently being conducted may shed more light on this subject.

One may also note the large difference in δ parameter values (the elevation of the weighting function) between the two studies. Specifically, there was a large difference between Random group mean δ values for Experiment 1 ($\delta = 1.397$) and Experiment 2 ($\delta = 0.695$). One main difference between the designs of Experiment 1 and Experiment 2 arose in the differing locations that the experiments took place. Whereas Experiment 2 administered the task to participants one and a time in an isolated lab room, Experiment 1 administered the task to three participants at a time in a small computer lab divided by partitions. Although each computer was confined in its own cubicle and participants worked individually, all three participants were able to hear the progress of the other two participants on their respective computers. One explanation for the increased attractiveness of bets in Study 1 could be that participants were being unintentionally influenced by the sounds of activity around them, which in turn may have affected their decision making behavior by adding pressure to the environment. Ongoing research is investigating the effects of time pressure on decision making in the prospect theory framework. That study appears to confirm these suspicions; time pressure leads to a higher δ parameter value for the weighting function, which indicates an increased overweighting of probabilities.

Future studies should extend the present experiments with a wider probability scale in order to defend the hypothesized full-scale weighting functions proposed. Presently, the lab is conducting a study that investigates both decision making behavior from a PT framework and the confidence-accuracy relationship from an individual differences approach.

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Figure 1a: Typical prospect theory value function

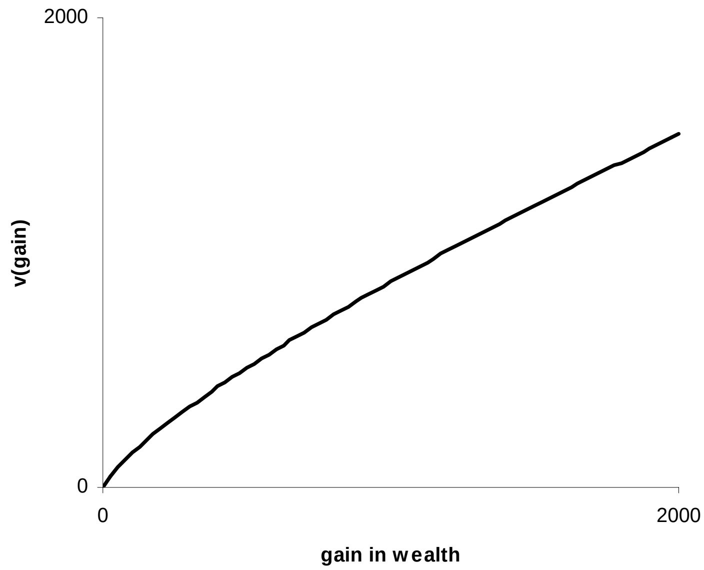


Figure 1b: Typical prospect theory weighting function

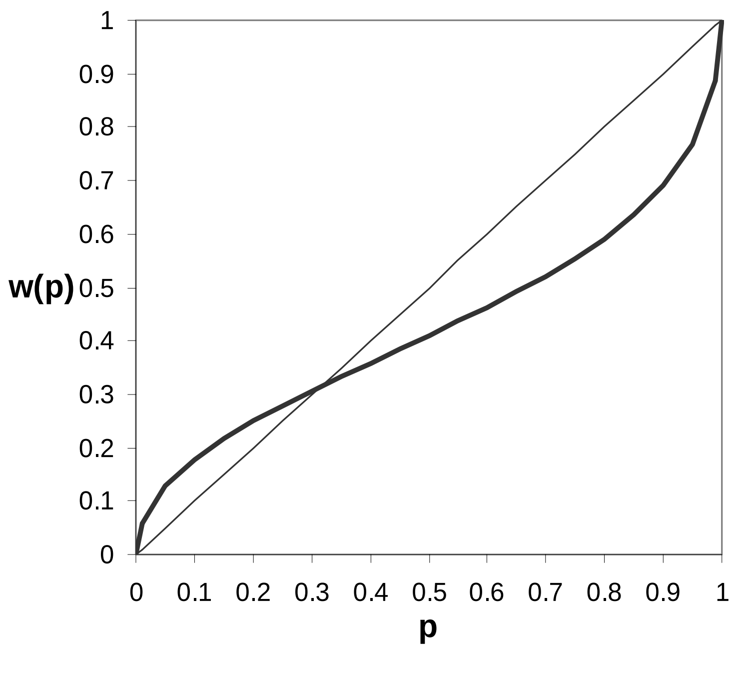


Figure 2a: Computer display of Experiment 1 betting format for "Random" group

For the bet now under consideration:

If you win:	Gain $25
If you lose:	Gain $0
Probability of win:	95%

Put an X on the SMALLEST amount you would accept rather than accept the bet.

$25

$20

$15

$10

$5

$0

Click here to proceed to the next screen.

Figure 2b: Computer display of Experiment 1 betting format for "Control" group

For the bet now under consideration:

If you were right:	Gain $25
If you were wrong:	Gain $0

Your answer: **New York** has a larger population than **Alabama**

Put an X on the SMALLEST amount you would accept rather than accept the bet.

$25

$20

$15

$10

$5

$0

Click here to proceed to the next screen.

Figure 3: Experiment 1 graph of CE differences across 7 probabilities

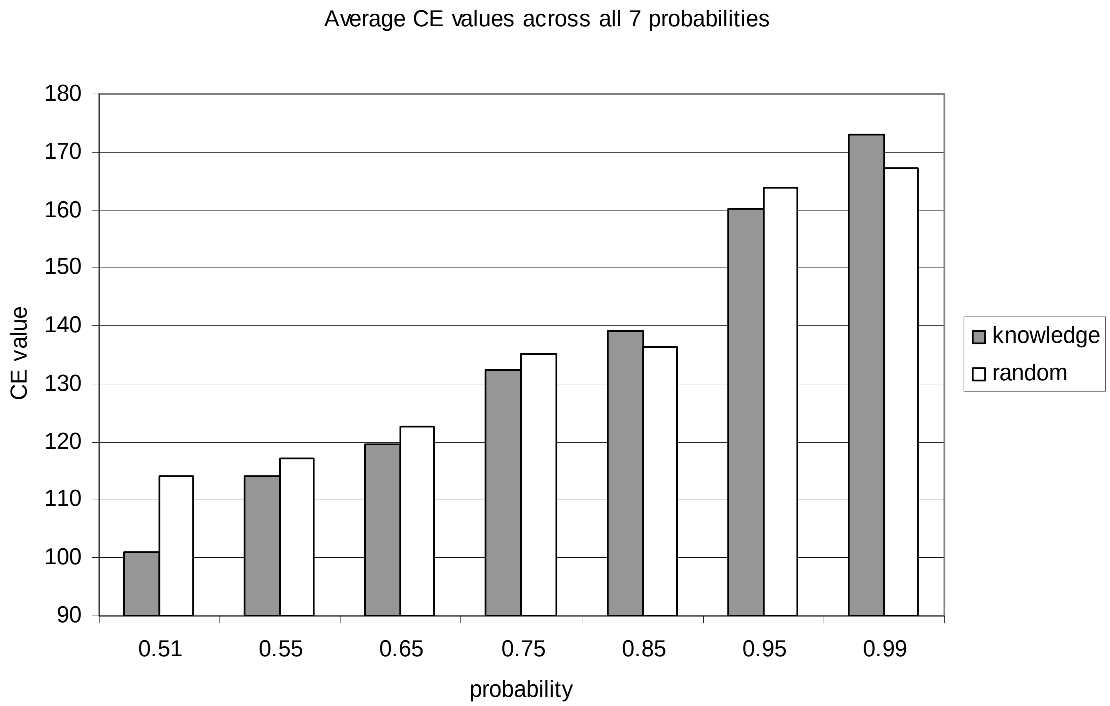


Figure 4 : Experiment 1 value function curves

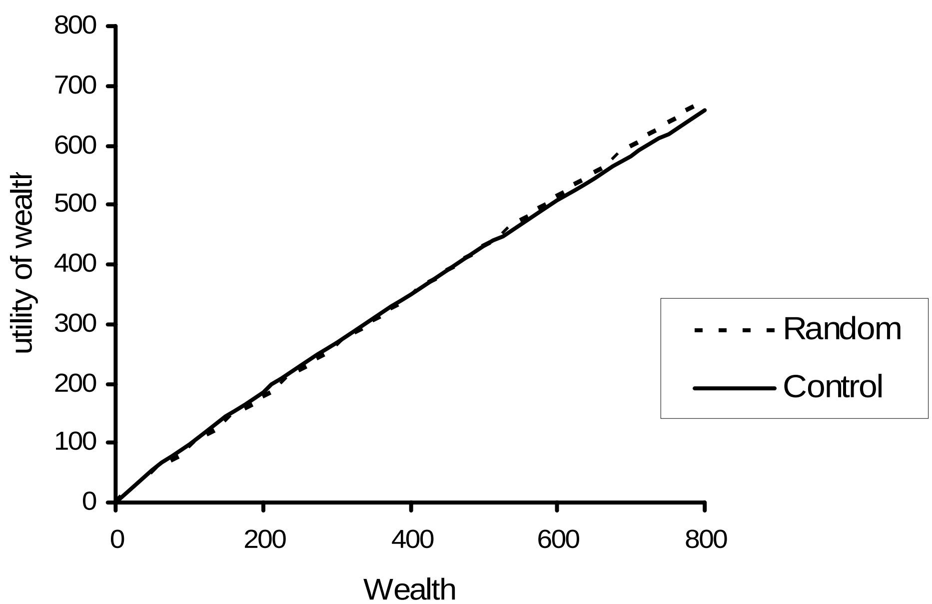


Figure 5a: Experiment 1 partial weighting function curve

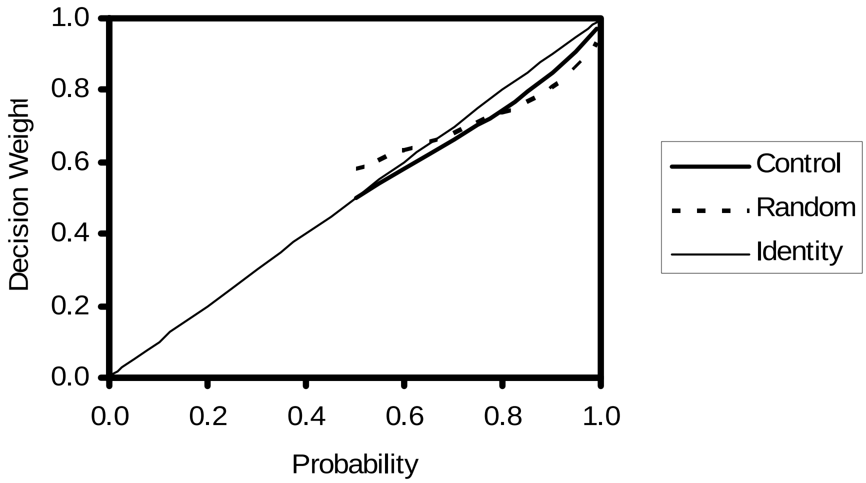


Figure 5b: Experiment 1 hypothetical full-scale weighting function curve

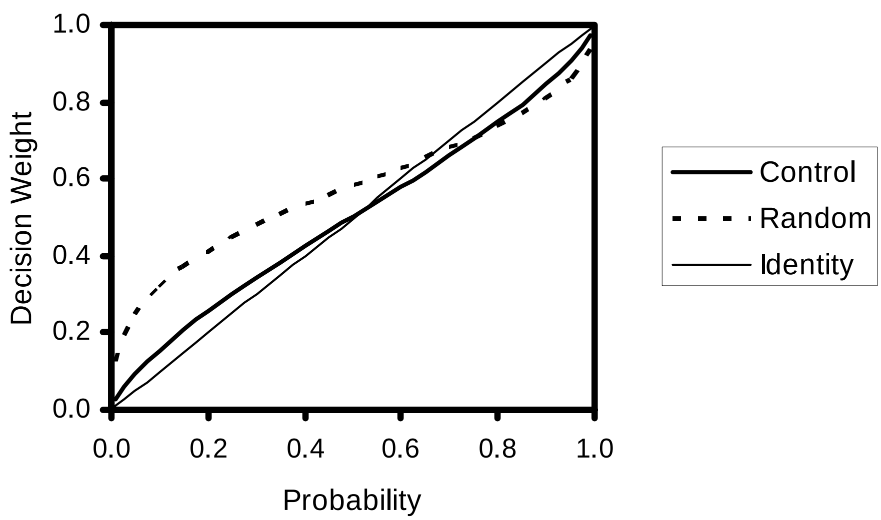


Figure 6a: Computer display of Experiment 2 betting format for "Random" group

For the bet now under consideration:

Win:	Gain $25
Lose:	Gain $0
Probability of win:	95%

Sure Thing	**Prefer Sure Thing**	**Prefer Bet**
$25	☐	☐
$20	☐	☐
$15	☐	☐
$10	☐	☐
$5	☐	☐
$0	☐	☐

Click here to proceed to the next screen.

Figure 6b: Computer display of Experiment 2 betting format for "Control" group

For the bet now under consideration:

Make the Putt:	Gain $25
Miss the Putt:	Gain $0
Putt Probability:	95%

Sure Thing	**Prefer Sure Thing**	**Prefer Bet**
$25	☐	☐
$20	☐	☐
$15	☐	☐
$10	☐	☐
$5	☐	☐
$0	☐	☐

Click here to proceed to the next screen.

Figure 7: Experiment 2 graph of CE differences across 7 probabilities

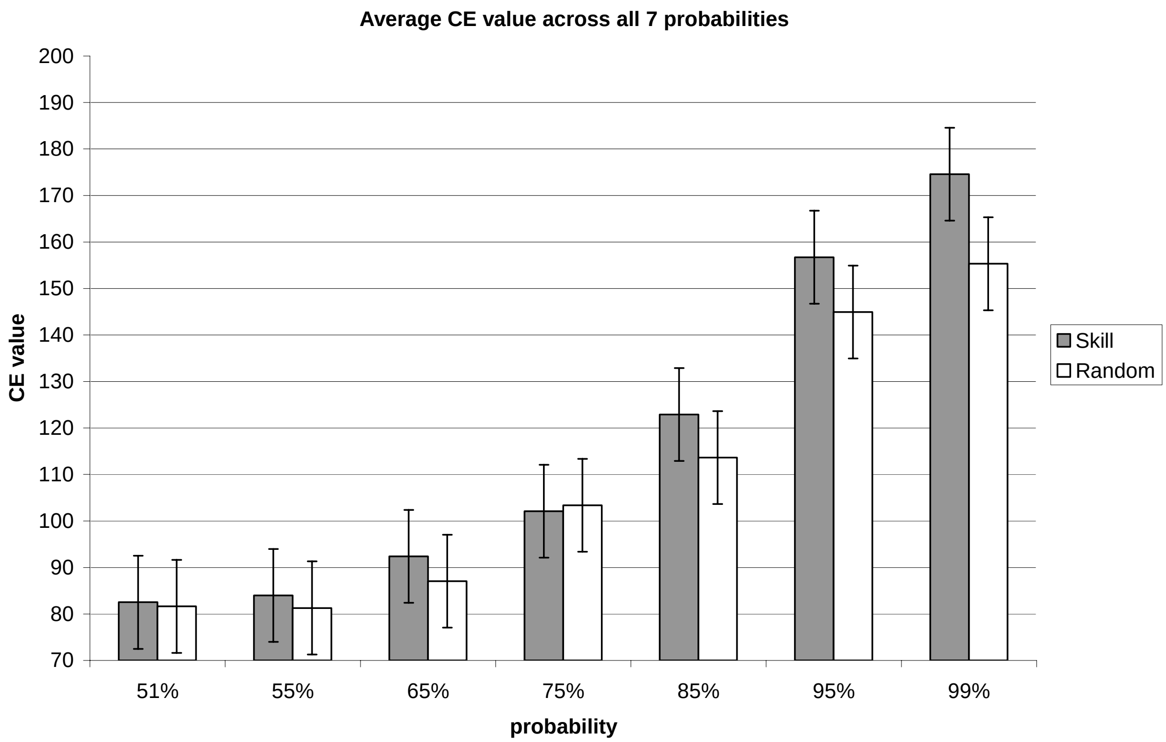
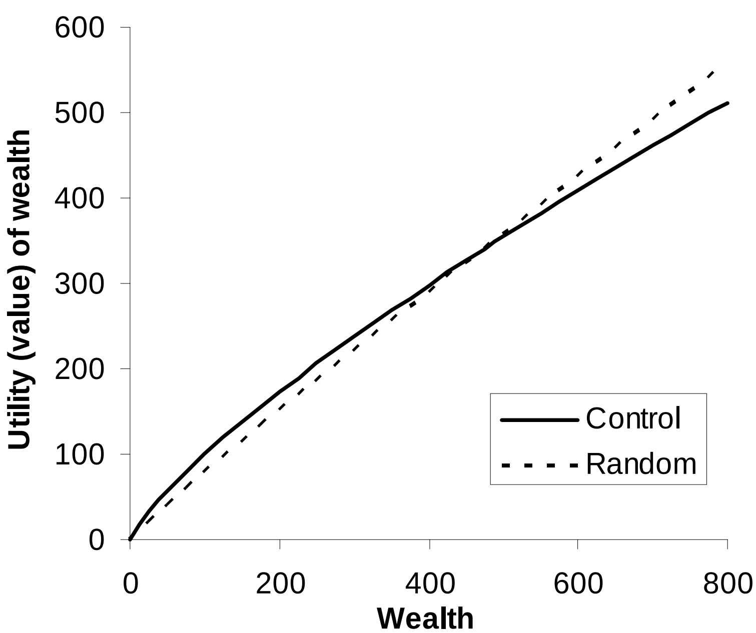


Figure 8: Experiment 2 value function curves



(a)

Figure 9a: Experiment 2 partial weighting function curves

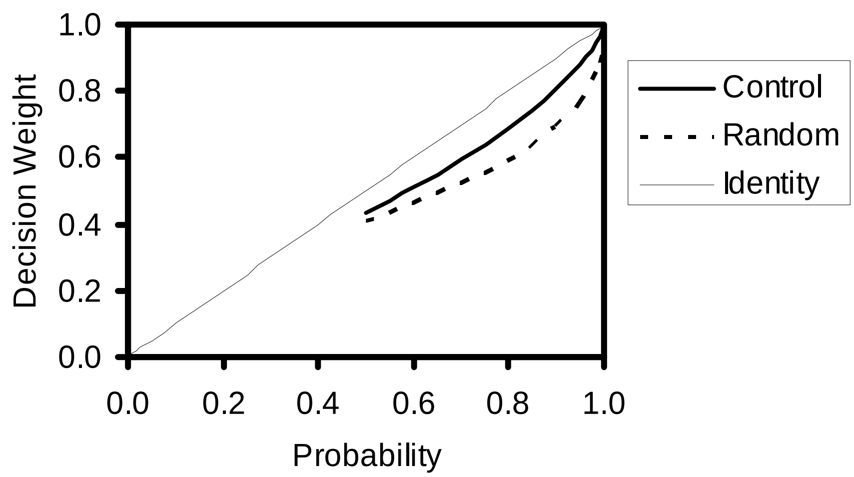


Figure 9b: Experiment 2 hypothetical full-scale weighting function curve

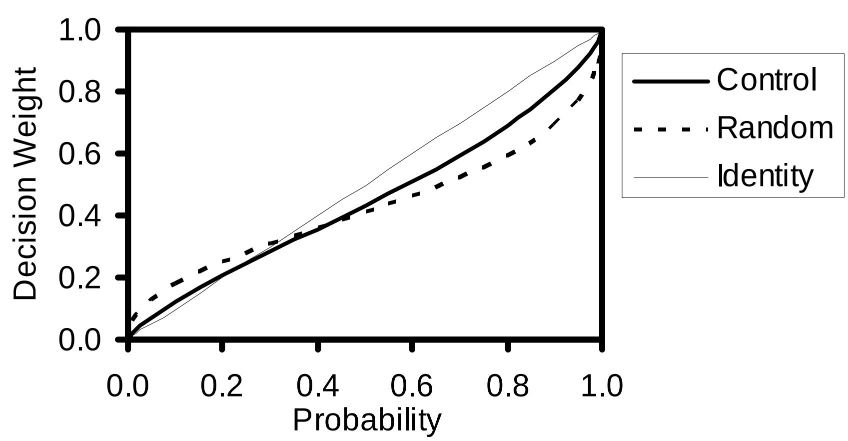


Table 1: Chart of 105 bets offered to all participants

	Probabilities							
Win-Loss Amounts		.51	.55	.65	.75	.85	.95	.99
	25-0							
	50-0							
	75-0							
	100-0							
	150-0							
	200-0							
	400-0							
	800-0							
	50-25							
	75-50							
	100-50							
	150-50							
	150-100							
	200-100							
	200-150							