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Modeling the Impact of Control on the Attractiveness of Risk in a Prospect Theory Framework

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ABSTRACT

Many decisions involve a degree of personal control over event outcomes, which is exerted through one's knowledge or skill. In three experiments we investigated differences in decision making between prospects based on (a) the outcome of random events and (b) the outcome of events characterized by control. In Experiment 1, participants estimated certainty equivalents (CEs) for bets based on either random events or the correctness of their answers to US state population questions across the probability spectrum. In Experiment 2, participants estimated CEs for bets based on random events, answers to US state population questions, or answers to questions about 2007 NCAA football game results. Experiment 3 extended the same procedure as Experiment 1 using a within-subjects design. We modeled data from all experiments in a prospect theory (PT) framework to establish psychological mechanisms underlying decision behavior. Participants weighted the probabilities associated with bets characterized by control so as to reflect greater risk attractiveness relative to bets based on random events, as evidenced by more elevated weighting functions under conditions of control. This research elucidates possible cognitive mechanisms behind increased risk taking for decisions characterized by control, and implications for various literatures are discussed. Copyright © 2009 John Wiley & Sons, Ltd.

KEY WORDS decision making; prospect theory; control; knowledge; probability; choice

INTRODUCTION

Most prominent decision research focuses on risky prospects in which the possible outcomes are completely dependent upon chance events. As Starmer (2000) notes, examinations of decision behavior gained momentum in the 18th century following the development of Expected Utility Theory (Bernoulli, 1954), which became the standard theory upon which the vast majority of individual choice research was based. Bernoulli set the stage of decision research by focusing on wagers based on coin flips and other strictly

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random events. As the field expanded to find more comprehensive explanations of choice behavior beyond EUT, researchers continued to study behavior in similar contexts, where the outcomes of events were still based on random events such as coin flips, decks of cards, or poker chips selected from a backpack. However, decisions that people make in the natural environment often involve some degree of personal control over the outcomes, for example driving a car, playing a game of Trivial Pursuit®, or going up to bat in a softball game. The present experiments directly investigated differences in decision behavior between random prospects and prospects characterized by control.

This paper is organized as follows. In the Introduction we discuss the definition of control and prior findings that suggests that situational control leads to increased risk taking; describe and justify a model of choice behavior based on PT; and summarize the designs of three experiments that directly assess the effect of control on various components of risk taking as modeled within a PT frame. The next three sections present three experiments which extend the risk-taking findings of research akin to Goodie and Young (2007) to the PT framework of choice behavior in an effort to better examine the cognitive mechanisms by which control affects decision making. Finally, in the General Discussion we discuss the implications of the present findings for various disciplines, note limitations of the present methods, and speculate on the future direction of research on decision making and control.

Previous findings in control and decision making

There is a literature of research involving conditions of control or the perception of control, generally integrated with psychology subfields such as health psychology, social psychology, and personality (Bandura, 1977; Miller, 1979; Rotter, 1966; Thompson, 1981; Taylor & Brown, 1988, 1994). Within these contexts, control is typically defined only vaguely. For the current research, we define control as ‘‘probability alterability’’ (Goodie, 2003); if people can positively alter the success rate of a given task, then that task is characterized by control. For example, because one can increase the odds of making a basketball free throw by practicing, shooting free throws is a task characterized by control. On the other hand, winning in a game of roulette is based completely on random events. One cannot take steps to increase the odds of winning beyond the operative probabilities; so, playing roulette is not characterized by control.

A number of studies have examined various contexts in which perceived control affects judgmental processes. In one branch of research, perceived control has been found to play a significant role in the degree of confidence associated with, or acceptance of, the potential outcomes of various life events. Weinstein (1980) posited that the degree of perceived controllability influences the amount of optimistic bias evoked by different events. When individuals rate events as having high perceived controllability, they rate their chances of success for those events with positive outcomes as above 50%, while they rate their chances of success for those events with negative outcomes as below 50%. When asked which kind of risky medical operation they would rather accept, participants are more willing to accept a surgeon’s skill over a random, but equivalent, chance of success with an alternative procedure that is performed by a machine (Brandstätter & Schwarzenberger, 2001). People are more overconfident in the accuracy of their responses when answering questions about past events, which can be studied, than about future events, which cannot be studied (Wright, 1982). One major conclusion that can be drawn from these investigations is that the perception of control leads to increases in judgments of confidence and optimistic bias; further, both of these effects on judgments suggest that situational control would increase risk-taking.

Similarly, some choice studies have directly examined effects of perceived controllability on gambling behavior, and they generally suggest that situational control leads to greater willingness to accept risk. Participants accept bets more often and express more confidence in chance bets when the situation incorporates the façade of a skill element, inducing an ‘‘illusion of control’’ (Langer, 1975). Similarly, participants change their betting behavior under skill-relevant manipulations but not under skill-irrelevant manipulations (Chau & Phillips, 1995). In other studies, participants favored betting on questions about

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subject matter in which they felt competent rather than on random chance events (Heath & Tversky, 1991; Taylor, 1995). Dixon, Hayes, and Ebbs (1998) found that people are willing to forfeit money for the opportunity to engage in superstitious activities that give the illusion of control, thereby decreasing their overall winnings. Recently, our own choice research has revealed that participants accept bets more on the outcomes of events characterized by control than on the outcomes of random events (Goodie, 2003; Goodie & Young, 2007). The conclusion to be drawn from this research is that a positive relationship exists between perceived control and the acceptance of risk in choice behavior. These results lend weight to the proposition that individuals assess risk—and subsequently make choices—differently if perceived control plays a role in the outcome of events.

Modeling decision behavior

In spite of the literature noting changes in overall judgment or decision behavior, relatively little progress has been made in elucidating the cognitive mechanisms by which control affects decision making. In the current study we utilize a framework based on PT (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), along with more recent advances, to examine specific aspects of decision making affected by control in a gains-only scenario. PT takes into account the subjective value attributed to a given change in wealth (a value function v) and the subjective weight attached to the probability of an outcome (a weighting function w). We model a certainty equivalent (CE) value according to both the utility of the bet's outcomes and the weighting of the bet's probabilities. The formulation used in PT for this set of prospects is

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

where p represents the probability of a win, and X and Y equal the outcome of a win and loss, respectively, in a two-option bet.

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

$$v(X) = \theta X^{\alpha} \tag{2}$$

Here, α describes the degree of curvature in the value function, representing the degree to which the value of a gain or loss in wealth changes as a function of that change in wealth (Figure 1a). θ is a scaling parameter that typically has no psychological interpretation. As can be seen in Figure 1a, the rate of change in the utility of gains decreases in magnitude the farther away the gain is from a neutral reference point; this is accomplished mathematically by taking v to be a power function of the win outcome X.

The probability weighting function is a regressive, inverse-S shaped curve, under which people overweight small probabilities and underweight medium-to-large probabilities (Figure 1b). Several conceptions of the probability weighting function exist (for a survey of functional formulations of probability weighting, see Stott, 2006). We use Gonzalez and Wu's (1999) specification of the weighting function for prospects in the domain of gains. The major advantage of using this weighting function rather than alternative mathematical formulations (e.g., that proposed by Prelec, 1998) is that it allows for plausible psychological interpretations of the discriminability and attractiveness of probabilities to an individual

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}} = \{1 + (\delta O^{\gamma})^{-1}\}^{-1} \tag{3}$$

where $O = p/(1-p)$ denotes the odds of winning. In Equation (3), γ represents discriminability (the curvature parameter) between probabilities and δ represents probability attractiveness (the elevation parameter). A weighting function with discriminability near 1 is close to linear, so that, throughout the probability scale, increases in objective probability are met with commensurate increases in weight. A

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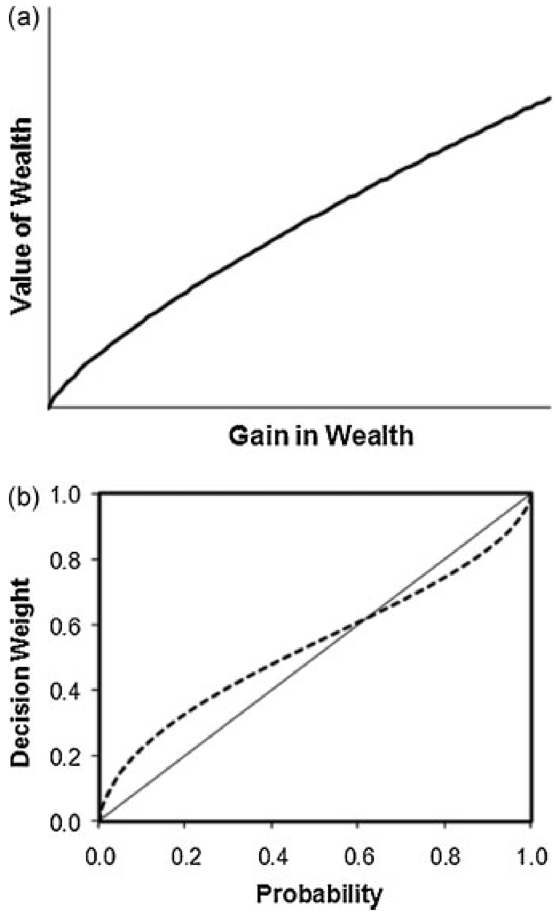

Figure 1. Typical prospect theory (a) value function with respect to gains and (b) weighting function

function with low discriminability is more curved, increasing sharply near the endpoints, but nearly flat in the middle. This type of weighting function reflects greater overweighting of low probabilities, greater underweighting of high probabilities, and lesser ability to discriminate among intermediate probabilities. A weighting function with high attractiveness (δ) rises quickly from zero and remains relatively elevated across the probability spectrum. Higher probability attractiveness would be associated with higher risk acceptance across the probability spectrum.

We fitted both the Gonzalez and Wu (1999) weighting function and another widely used 2-parameter weighting function (Prelec, 1998) to preliminary data in a comparison of model fit. Results found no significant differences in model fit between the two functions as evidenced by nearly equivalent concordance coefficients, and the Gonzalez and Wu (1999) model was retained for use in future studies due to its interpretational advantages.

For the present research, participants' data are elicited as CE rather than the value of CEs $v(\mathrm{CE})$ as Equation (1) requires. However, by substituting the value function (2) into Equation (1), and taking the natural logarithm, we obtain

$$\log(\mathrm{CE}) = \alpha^{-1} \log[w(p)X^{\alpha} + \{1 - w(p)\}Y^{\alpha}]$$

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Substitution of Equation (3) and further algebraic simplification leads to a model of decision making suitable for nonlinear regression analysis

$$\log(\mathrm{CE}_{ijk}) = \alpha_{ij}^{-1} \log\left[\frac{(X_{ijk}^{\alpha_{ij}} - Y_{ijk}^{\alpha_{ij}})}{\{1 + (\delta_{ij} O_{ijk}^{\gamma_{ij}})^{-1}\}} + Y_{ijk}^{\alpha_{ij}}\right] + e_{ijk} \tag{4}$$

where CE_{ijk} denotes the CE elicited on the *k*th bet given to the *j*th subject in the *i*th experimental condition and the e_{ijk}s are normally distributed random errors.

In an ingenious study utilizing actual responses from contestants on the television gameshow ‘‘Deal or No Deal,’’ researchers examined the efficacy of modeling naturalistic decisions with a PT framework rather than an expected utility framework (Post, van den Assem, Baltussen, & Thaler, 2008). Their model comparisons revealed that PT provided a more appropriate descriptive framework for the systematic fluctuations in risky choices that the gameshow contestants made. Their findings suggest that PT can successfully account for naturalistic decisions involving real monetary incentives. It also reflects an ideal test of real-world decisions involving little or no control, as the rules of the ‘‘Deal or No Deal’’ transparently reveal it as a game of random draws. The present research extends this principle to decisions that involve a more pronounced element of control. Modeling each participant’s data within the PT framework permits analyses of differences in risk taking patterns between groups based on control. Differences in α (i.e., $\alpha_{10} \neq \alpha_{20}$) would indicate a difference in the way possible gains in wealth are valued. Differences in γ would indicate differentially nonlinear weighting of probabilities. Differences in δ would suggest differences in the overall attractiveness of risk. Examples of probability weighting functions with high and low values of δ, and high and low values of γ, are depicted in Figures 2a and b, respectively.

Comparing uncertain outcomes to objective probabilities

The present studies directly compare bets based on objective probabilities (random events) to bets based on uncertain, ambiguous outcomes (confidence in answers to general knowledge questions). The terms ambiguity and uncertainty are used essentially interchangeably in the decision-making literature to describe outcomes whose probabilities are unknown. When encountering uncertainty in a prospect, decision makers rely on likelihoods to assess subjective probability estimates of the outcomes.

Recently, researchers have argued for the efficacy of modeling decision behavior in the domain of uncertainty with the same approach as in the domain of risk (Fox & Tversky, 1998; Kilka & Weber, 2001; Tversky & Fox, 1995; Wu & Gonzalez, 1999; Wakker, 2004). Tversky and Fox (1995) asked participants to estimate CEs for uncertain prospects such as the outcomes of future basketball games, the future temperature in a nearby major city, and the future value of the Dow-Jones index, as well as pure chance gambles with objective probabilities; Tversky and Fox then interpolated CE estimates into a model based on PT. Their results showed that likelihood assessments for uncertain outcomes, when transformed into decision weights on a probability scale, behave much like decision weights for objective probabilities, with an inverse-S shaped function that satisfies bounded subadditivity. Fox and Tversky (1998) later conceptualized the two-stage model of decision making under uncertainty, which argues that one can transform beliefs about the uncertain probability of success of events onto the same risky weighting function used for objective probabilities. The present study relies on this premise in that it directly relates decisions under uncertainty with decisions under risk by asking participants to estimate their confidence in the success of skill-based and knowledge-based tasks, not just future uncertain outcomes based on chance.

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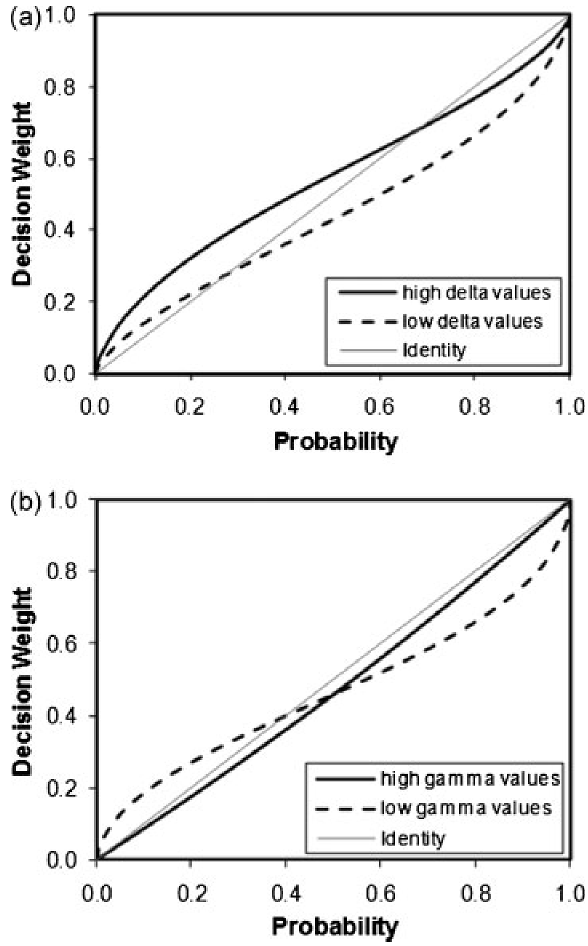

Figure 2. Hypothetical depictions of various probability weighting functions with (a) changes in estimated δ (''delta'') values and (b) changes in estimated γ (''gamma'') values. Differences in δ values reflect changes in the attractiveness of probabilities, while differences in γ values indicate changes in probability discriminability

The present research

The literature on control (e.g., Goodie, 2003; Langer, 1975; Weinstein, 1980) often suggests that control makes risk generally more attractive. This would suggest that control may have a differential effect on the overall attractiveness of probabilities associated with the risk, represented by the δ parameter. By formally modeling decisions with and without control, we sought to test whether this is the case, or whether the effects are located elsewhere. However, as no quantitative modeling of the illusion of control has been conducted prior to this research, we did not make an initial prediction that control would lead to specific differences in δ or in the two other parameter values of interest (γ or α).

The basic design of all three experiments was as follows: (a) participants answered general knowledge questions and provided subjective assessments of confidence in their answers, and (b) participants then estimated the equivalent cash value of various bets based on their answers to the general knowledge questions. These equivalent cash values of bets, *CEs*, were then modeled within the probability weighting functions and value functions to arrive at group-level parameter estimates of α, γ, and δ. In Experiments 1 and 3, participants assessed the equivalent cash value of betting on their answers to trivia questions

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concerning US state populations. In Experiment 2 they assessed the equivalent cash value of betting on answers to either US state populations or NCAA college football game results. In all three experiments, a comparison group assessed the equivalent cash value of betting on random events that were matched to the experimental groups' knowledge bets. (In Experiment 3, the manipulation was performed within-subjects.) Do situations characterized by control lead individuals to accept risk more than situations not characterized by control, as previous research suggests? Additionally, are the differences in their risk taking attributable to specific components of decision behavior, such as probability attractiveness, probability discriminability, or the valuation of outcomes?

EXPERIMENT 1

In Experiment 1 we assessed whether participants evidenced a difference in decision making behavior when betting on their knowledge versus betting on random events in the nonlinearity of their value functions, the discriminability of probabilities, or the attractiveness of risk. In this between-subjects design, participants encountered bets based on either the outcome of a lottery game in the "Random" condition or the correctness of their answers to questions concerning US state populations in the "Knowledge" condition. The Georgia Gambling Task (GGT; Campbell, Goodie, & Foster, 2004; Goodie, 2003; Goodie & Young, 2007) was modified for the present experiments. The original GGT first asked participants to answer general knowledge questions and estimate their confidence in all answers. Then, participants were given the choice to either accept or reject bets based on their answers to the general knowledge questions. All bets in the GGT were constructed to be fair, having zero average marginal value if the participants' confidence was well calibrated to their accuracy. The modification of the GGT for the present research allowed for the estimation of CEs for each bet. The design of Experiment 1 allowed for us to examine how people assess bets with possible outcomes that are both likely—greater than 50% chance of winning—and less than likely—less than 50% chance of winning. This experiment utilized six confidence categories and 12 possible two-outcome pairs (involving both a high and a low dollar amount), yielding up to 72 bets for all participants.

Method

Participants

Twenty-two participants (Random = 11, Knowledge = 11) were recruited for Experiment 1. Participants for all three experiments were recruited from the Research Pool of the Psychology Department at the University of Georgia in exchange for partial psychology course credit. Experimenters studied up to three participants at a time at individual computer workstations. Those who had previously participated in related experiments were excluded.

Procedure

For Phase 1, all participants answered questions about US state population and assessed their confidence in each answer. For every question, participants were asked to choose which of six randomly chosen US states had the highest population. State population was based on the 2005 Census Bureau estimate. General knowledge question selection for use in decision-making research has been a contentious topic (Juslin, 1994; Juslin, Winman, & Olsson, 2000). In the present studies, we used a well-defined domain to create a pool of items that would have varying inter-item confidence estimates within most participants. This question type has been successfully utilized in previous experiments (Goodie & Young, 2007). The following is an example question that a participant might have encountered.

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Which of the following six US states has the highest population, according to the 2005 US Census Bureau?

Arizona Michigan Texas Rhode Island Idaho Oregon

In this case, a pure guess for a question would indicate approximately 17% confidence in any answer. All questions were presented in a random order. The second question in Phase 1 asked participants to assess their confidence in each of their answers with one of the following six categories [20, 35, 50, 65, 80, 95%]. We chose these confidence categories to allow for a relatively proportional division of the range of possible probabilities. Participants answered 100 US state population questions of this type. In the process of answering all 100 questions, a participant would likely express, for example, 50% confidence in multiple answers. Because that participant may not feel exactly 50% confident in all of those answers, the last portion of Phase 1 displayed a variety of the participant's 50% confidence answers and asked the participant to choose among those options one answer that best exemplified an answer in which he/she was truly 50% confident. This same question was asked for all six confidence categories.

In Phase 2, participants in both the conditions estimated CEs for as many as 72 bets. A participant in the Knowledge condition may have encountered fewer than 72 bets if, for instance, he/she never felt 20% confident in any of the 100 state population questions; in that case, that participant would only estimate CEs for 60 out of the 72 possible bets. A CE is a dollar amount that, if provided with certainty, the participant views as equivalent in subjective value to a bet. The 72 bets were obtained by crossing the six probability levels with 12 two-outcome pairs adopted from Gonzalez and Wu (1999): the two-outcome pairs were (in dollars) 25–0, 50–0, 100–0, 150–0, 200–0, 400–0, 800–0, 50–25, 75–50, 100–50, 150–100, 200–150. Note that a ''loss'' of any bet consists of either no change in wealth, or an absolute gain, which is a loss only in the sense of being a smaller gain than would have been obtained in the event of a win. We adopted 12 of the 15 two-outcome pairs used by Gonzalez and Wu (1999) in order to create similar circumstances for our own procedure and paradigms as a means of a cross-check with their initial findings, while also endeavoring to avoid fatigue in our undergraduate participants. Each bet displayed the amount of money gained for a win, the amount of money gained for a loss, and the parameters of the bet.

For the Knowledge condition, the outcome of each bet was determined by the correctness of participants' answers to the US state population questions; correct answers resulted in a win and incorrect answers resulted in a loss. Because participants in the Random condition were encountering bets based on random events, each bet outcome was dependent upon probabilistic chances, not their answers to their answers in Phase 1; however, all confidence categories that were utilized in Phase 1 of the experiment were presented as the probabilistic odds for the random chance bets. All participants estimated CEs to the nearest dollar using Gonzalez and Wu's (1999) narrowing-down process. The narrowing-down process involves asking participants to compare a list of *sure thing* dollar amounts to a bet and decide, out of the sure things listed, the smallest amount that the participant would be willing to reject the specific bet for. After choosing the smallest sure thing that he/she is willing to accept in lieu of the bet, the participant then encounters a new, more constrained list of sure things to compare to the bet, and the process is completed again. This process is repeated until the participant estimates, within $1, the amount of money that is considered equivalent to the bet. An example of this narrowing down process is illustrated in Table 1.[1]

[1]Other CE elicitation procedures exist, and there is disagreement over the relative superiority of each. Bostic, Herrnstein, and Luce (1990), for example, compared two such procedures: one in which the different titrations toward an indifference point were transparent to the participant (as is used here), and one in which the titration process was hidden from participants so that the different titrations toward an indifference point were interweaved. The two processes yielded differing results, and Bostic et al. concluded that the hidden titration process provides a less biased CE estimate. We chose the CE elicitation method used in the present research because of the distinct advantages of consistency with the methods used previously in this specific line of research (e.g., Gonzalez & Wu, 1999; Tversky & Kahneman, 1992).

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Table 1. A hypothetical example of the narrowing-down process for CE estimation for a bet with a 50% chance of winning \$25 or \$0 otherwise. The tables describe both (a) the first screen in the narrowing process and (b) the last screen. In this experiment, the participant estimated a CE of \$17 for this bet

What is the smallest amount of money you would be willing to accept rather than the bet?	
(a)	
\$25	
\$20	
\$15	x
\$10	
\$5	
\$0	
(b)	
\$20	
\$19	
\$18	
\$17	x
\$16	
\$15	

Although all bets in Experiment 1 were played for hypothetical money, experimenters requested that participants think through each wager as if the wagers could be played out at full face value.

Modeling

We modeled subject specific parameters via mixed effects: $\alpha_{ij} = \alpha_{i0} + a_{ij}$, $\gamma_{ij} = \gamma_{i0} + c_{ij}$, $\delta_{ij} = \delta_{i0} + d_{ij}$, where $\alpha_{i0}, \gamma_{i0}, \delta_{i0}, i = 1, 2$, are fixed population-level parameters, and a_{ij}, c_{ij}, d_{ij} are subject-specific random effects assumed to jointly follow a multivariate normal distribution with zero mean and a common 3×3 variance-covariance matrix $\Phi = (\phi_{st}); s = 1, 2, 3; t = 1, 2, 3,$ which is estimated from the data without assuming any simplifying structured form. Random subject effects are assumed independent across subjects and independent of model errors $\mathbf{e}_{ij} = (e_{ij1}, \ldots, e_{ijn_{ij}})'$, which are assumed multivariate normal with mean zero and variance–covariance matrix Σ_{ij}. To account for non-constant variance and correlation observed in the data, the within-subject error variance–covariance matrix Σ_{ij} was modeled with an ARMA correlation structure (autoregressive-moving average; Pinheiro & Bates, 2000), and, because of much greater observed variability for bets involving a zero loss amount, two distinct error variance parameters depending upon whether $Y_{ijk} = 0$. Both residual autocovariance function plots and AIC goodness of fit statistics were used to choose a specific ARMA model, with the AR(1) (autoregressive of order 1) correlation model selected in each case. Thus the diagonal elements of Σ_{ij} are $\mathrm{var}(e_{ij1}), \ldots, \mathrm{var}(e_{ijn_{ij}})$ where $\mathrm{var}(e_{ijk}) = \sigma_1$ if $Y_{ijk} = 0$ and $\mathrm{var}(e_{ijk}) = \sigma_2$ otherwise, and n_{ij} denotes the number of observations for the *i,j*th subject. Off-diagonal elements of Σ_{ij} are covariances among within-subject errors and, when rescaled as correlations, are determined by an AR(1) structure—that is, $\mathrm{corr}(e_{ijk}, e_{ijl}) = \rho^{|k-l|}$. Note that Σ_{ij} is subscripted by *i,j* because its dimension may differ across subjects, but is not subject-specific in the sense that its functional form is the same for all subjects and it depends only on parameters assumed common to all subjects.

To assess the goodness of fit of our models, we report the concordance correlation coefficient of Vonesh, Chinchilli, and Pu (1996). This statistic, which is closely related to R^2, is a measure of agreement between observed and predicted values according to the model, for which concordances near the theoretical maximum of 1 indicate close agreement.

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Tests of hypotheses of no difference across experimental conditions in α, γ, and δ were conducted using approximate F tests as described in Pinheiro and Bates (2000, Sec.7.2.2) which are suitable for inference on hypotheses of the general linear form $H_0 : \mathbf{C\beta} = \mathbf{d}$ for regression parameter vector $\boldsymbol{\beta}$, any matrix of constants $\mathbf{C}$, and constant vector $\mathbf{d}$. The models used here are examples of nonlinear mixed-effects models; for more on this class of models, their use in modeling repeated measures data like those from the current experiments, and statistical methods of estimation and inference in this class using the S-PLUS nlme library, see Pinheiro and Bates (2000).[2]

Results and discussion

During the betting phase of these experiments, participants may fail to follow basic laws of consistency, dominance, monotonicity, or transitivity [e.g., if a participant that views a gamble with $p(\text{win}) = .50$ as more attractive than the same gamble outcomes with $p(\text{win}) = .99$] due to inattention during the task. If a participant clearly demonstrated a lack of any internal consistency in these terms, the participant was removed from analysis. Based on these violations, we removed one participant from the Knowledge condition prior to analysis. We computed results by analyzing participant CE data using the nonlinear mixed effect model (Equation (4)), which allows distinct parameters by treatment for both the generally accepted value function (α) and the Gonzalez and Wu (1999) probability weighting function (γ and δ). The fitted model had a concordance correlation coefficient of 0.941, indicating good fit to the data. Parameter estimates and standard errors for Experiment 1 are reported in Table 2.

We did not form a priori hypotheses regarding the effects of control on the three parameter values. As such, we conducted a Bonferroni correction on the following significance tests to account for potential comparison-wise Type-I error. We compared CE responses from the Knowledge condition to those from the Random condition. All three parameter estimate comparisons were conducted, and a Bonferroni adjustment was made on all resulting p-values. The estimated δ value of the model for the Knowledge condition was significantly greater than that for the Random condition, (Knowledge = 1.492, Random = 0.881; $F(1,1306) = 12.75$, $p < .01$[3]). Estimated γ parameter values did not differ significantly between conditions: Knowledge = 0.546, while Random = 0.751 ($F(1,1306) = 1.26$, $p = .26$). Estimated α values differed between conditions (Knowledge = 0.794, Random = 0.979; $F(1,1306) = 4.07$, $p = .04$). After taking into account the Bonferroni correction, the Knowledge condition's estimated δ value remained statistically larger than that for the Random condition, but estimated α parameter values did not differ significantly between conditions. Both conditions, weighting and value functions are depicted in Figures 3a and b, respectively.

CE responses from participants in the Knowledge condition yielded a weighting function with a significantly higher estimated δ value than CE responses from people in the Random condition, supporting an overall difference in risk attractiveness when betting on events characterized by control versus random events. We did not observe a significant difference in the way people are able to discriminate among various probabilities, which would be the case if estimated γ values were significantly different between groups.

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[2]An alternative approach to the analysis of nonlinear models for repeated measures data such as those presented here is the two-stage approach. In two-stage modeling, model (4) would first be fit to the data from each subject separately and, in a second stage, the resulting subject-specific parameter estimates would then be combined using a population-level model such as an analysis of variance model to test for differences across conditions. Such an approach is somewhat less flexible than the nonlinear mixed effect models we use here and poses several challenges, including the appropriate modeling of correlation and non-constant variance in the within-subject data, problems of non-convergence of model fitting routines for some subjects' data, appropriate accounting for different levels of precision in the parameter estimates across subjects, and ease of implementation in existing software. See Davidian and Giltinan (1995, chaps 5–6) for a description of the two-stage and mixed effect modeling approaches and their pros and cons.

[3]As observed in Gonzalez and Wu (1999) and Tversky and Kahneman (1992), the design of a study that examines decision behavior from a prospect theory framework requires a large number of observations in order to permit assessments of probability weighting and utility at both the group and individual level. Furthermore, the factorial nature of the wagers (6 probabilities of a win crossed with 12 two-outcome pairs) allows for assessing how one aspect of decision behavior changes while holding one aspect of the wager constant (e.g., examining how CEs change as a function of $p(\text{win})$ while holding high and low outcomes constant).

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Table 2. Parameter estimates and standard errors for model (4) for Experiments 1–3

	Experiment 1			Experiment 2			Experiment 3		
Parameter	Condition	Estimate	SE	Condition	Estimate	SE	Condition	Estimate	SE
α_{10}	Knowledge	0.794	0.0677	Football	0.946	0.102	Knowledge	0.853	0.0425
α_{20}	Random	0.979	0.0616	Random	0.809	0.0447	Random	1.03	0.0436
α_{30}				States	0.842	0.0914			
γ_{10}	Knowledge	0.546	0.131	Football	0.657	0.117	Knowledge	0.768	0.0495
γ_{20}	Random	0.751	0.127	Random	0.708	0.0613	Random	0.782	0.0497
γ_{30}				States	0.641	0.117			
δ_{10}	Knowledge	1.49	0.133	Football	1.55	0.207	Knowledge	0.999	0.0952
δ_{20}	Random	0.881	0.107	Random	0.936	0.0989	Random	0.966	0.0952
δ_{30}				States	1.20	0.194			
σ_1		0.525			0.499			0.424	
σ_2		0.0966			0.108			0.0954	
ρ		0.113			0.0729			0.164	
$\mathbf{\Phi}$		$\begin{pmatrix} .0228 & .00319 & .0261 \\ & .153 & -.109 \\ & & .112 \end{pmatrix}$			$\begin{pmatrix} .0635 & .0265 & -.0563 \\ & .138 & -.0835 \\ & & .380 \end{pmatrix}$			$\begin{pmatrix} .0508 & .0000624 & .0256 \\ & .0767 & -.0625 \\ & & .323 \end{pmatrix}$	

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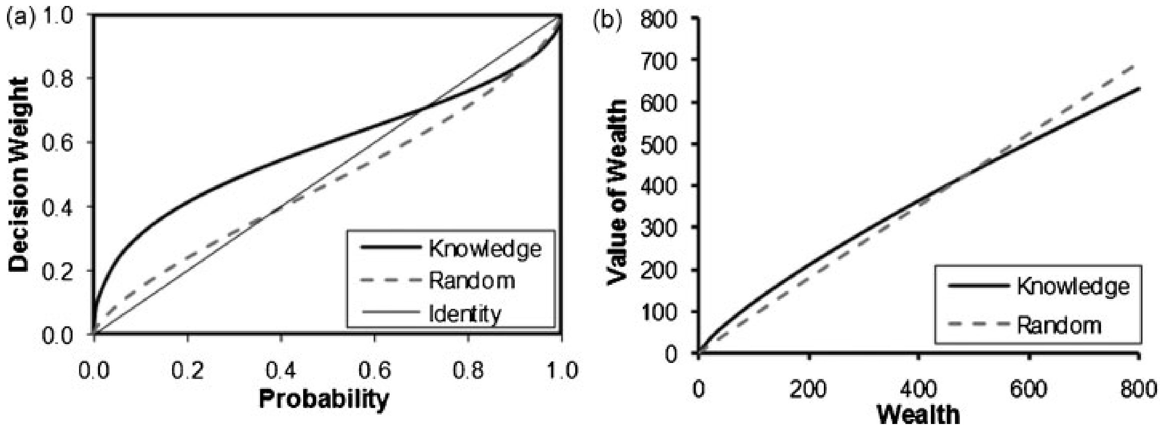

Figure 3. (a) Weighting function curves and (b) value function curves observed in Experiment 1 based on mean estimated δ, γ, and α values. "Probability" refers to the participant's believed probability (Fox & Tversky, 1998). For bets based on random events, this means the objective probability that is provided. For bets based on knowledge, this means the expressed confidence

Table 3. Averages of overall stated confidence, observed accuracy, and resulting overconfidence of general knowledge questions answered in Phase 1 of Experiments 1, 2, and 3

Experiment	Bet condition	Overall confidence	Overall accuracy	Overall overconfidence
1	Knowledge	0.556	0.547	0.009
	Random	0.536	0.504	0.032
2	Football	0.705	0.688	0.017
	Random	0.752	0.730	0.022
	States	0.762	0.775	−0.013
3	All participants	0.727	0.742	−0.015

Instead, as is shown in the weighting function figures for Experiment 1, the estimated weighting functions for the Knowledge condition is elevated above that of the Random condition.

Analyses involving overconfidence in answers to state population questions indicated no difference in average overconfidence in answers to general knowledge questions between betting conditions, as should be expected for the current experimental design (Table 3). Significant differences in overconfidence between the Random and Knowledge conditions would be surprising, as the data for assessing overconfidence were collected prior to the initiation of treatment differences. In this study, overconfidence for each participant is computed by subtracting observed accuracy in answers from average stated confidence. Overconfidence estimates within the range found for this experiment, as well as Experiments 2 and 3, suggest that individuals' estimates of confidence were relatively well calibrated to their true accuracy. A confidence calibration curve is depicted in Figure 4, which shows a typical pattern of underconfidence (confidence less than accuracy) at the lowest category and overconfidence (confidence greater than accuracy) at higher levels of confidence.

One of the key elements of the PT framework is its ability to describe the tendency for individuals to be loss averse such that, for a given risky prospect, potential losses loom larger than potential gains, and it is seen graphically in the value function which is normally convex for losses and concave for gains and generally steeper for losses than for gains. Tversky and Kahneman (1991, 1992) and others have noted that loss aversion drives much of the shape of PT's value function. However, in decision contexts that are strictly lossless (whereby $x > y > 0$), the shape of the resulting gains-only value function may reveal a more nearly

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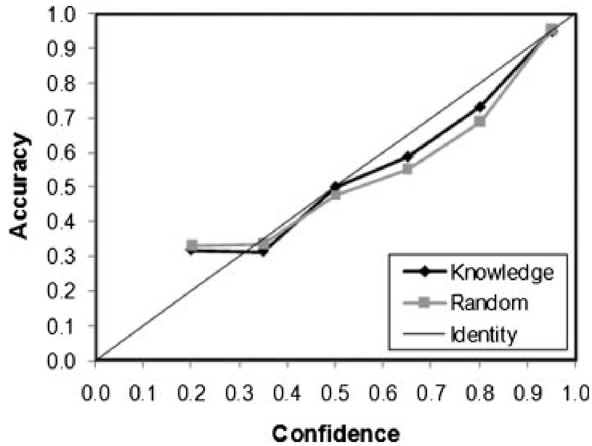

Figure 4. Confidence calibration curves observed in Experiment 1

linear curve. Indeed, in their direct comparison of the curvature of value functions for both mixed prospects and strictly positive prospects, Tversky and Kahneman (1992) found this to be the case, noting that "the curvature of the value function for gains is slight" (p. 310). Consistent with this observation, the present experiment's observed α values (Figure 3b), which drive the nearly linear curvature of each condition's value functions, reveal limited convexity.

Past decision research frequently suggested that control increases risk-taking in a generalized way such as would be implied by an increase in δ (Dixon et al., 1998; Langer, 1975; Weinstein, 1980). Experiment 1 results support this notion. As seen in Figure 3a, the difference in δ causes the weighting function for Knowledge condition to rise higher and remain higher than that for the Random condition across the probability spectrum.

Although our interest centers on δ, γ, and α, some explanation of the estimates of other model parameters in Table 2 may be useful here. As mentioned previously, greater error variability was observed for bets involving a \$0 lose amount (i.e., when $Y = 0$) than for those when $Y > 0$. Hence the inclusion of different error variances for these scenarios and the much larger estimated error standard deviation when $Y = 0$ ($\hat{\sigma}_1 = 0.525$) than otherwise ($\hat{\sigma}_2 = 0.0966$). The estimated autocorrelation parameter, $\hat{\rho} = 0.113$, indicates a small positive linear association between the CEs elicited on consecutive bets. The three diagonal elements of the estimated $\mathbf{\Phi}$ matrix are estimated subject-to-subject variance components for α, γ, and δ, respectively. The magnitudes of these values indicate substantially less heterogeneity among subjects in the value function than in the probability weighting function. Note that similar estimates and conclusions regarding σ_1, σ_2, ρ, and $\mathbf{\Phi}$ hold for Experiments 2 and 3, so hereafter we concentrate on the results regarding the parameters of primary interest, δ, γ, and α.

EXPERIMENT 2

To generalize the findings of Experiment 1, in Experiment 2 we included an additional condition that falls under the Knowledge condition alongside the US state population questions: NCAA college football knowledge. College football is popular among the University of Georgia undergraduates who made up our study population. Additionally, decision researchers have sampled this question domain and related question domains in similar ways with success, generally in an attempt to show that the observed effects are not domain-specific (Tversky & Fox, 1995). This between-subjects design thus included three conditions, which

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we label Random, States, and Football. Participants in the States and Football conditions both assessed bets with outcomes that are characterized by control in that winning or losing a bet in either condition depends upon one's knowledge. We made specific predictions for Experiment 2 in light of the results found in the previous experiment: estimated δ values for both Knowledge conditions should be significantly higher than those for the Random condition, whereas no significant differences should exist for the α or γ parameter values.

Method

Participants

Sixty-nine new participants from the same population as Experiment 1 were randomly assigned to one of three conditions (Random = 25, States = 22, Football = 22); experimenters studied up to three participants from the same condition at a time at personal computer workstations.

Procedure

In Phase 1, all participants answered 100 questions and assessed their confidence in each answer. Participants were randomly assigned to answer one of two types of knowledge questions: either Football questions or States questions.

The Football type of knowledge question displayed one of the 425 NCAA-Division I college football regular season conference games or BCS Bowl games played during the 2007 season, which extended to January 2008. At the time of the administration, this was the most recent season that had been completed. Each football question displayed the names of both football teams as well as the date and location of the game. The participants were asked to decide which football team won the game. The following is an example Football question that a participant might have encountered.

Which team won this game?

South Florida   Auburn

Date: 8 September 2007   Location: Auburn

Participants assigned the States type of question encountered 100 questions that asked for a binary comparison US state populations. This type of state population question was changed from the 6 state version in Experiment 1 in order to directly compare data from participants betting on football questions (which are inherently binary) to data from participants betting on US state population questions. The following is an example States question that a participant might have encountered.

Which state has the higher population according to the US Census bureau estimates for 2005?

New Jersey   Illinois

All participants were asked to assess their confidence in each of their answers with one of the following seven categories [51, 55, 65, 75, 85, 95, 99]. As in Experiment 1, each participant was asked to choose one question from each confidence category that best exemplified an answer in which he/she was truly XX% confident; these questions were utilized in Phase 2 for both the States and Football conditions.

For Phase 2, participants were assigned to one of three betting conditions: a Random condition, a Knowledge condition that encountered Football question bets, and a Knowledge condition that encountered

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States question bets. To ensure approximately equal numbers of participants in all conditions, the following procedure was carried out. Out of the participants who answered the Football questions, one-third was randomly assigned to the Random condition; all others were assigned to the Football condition. Out of those who answered the States questions, one-third was randomly assigned to the Random condition, while the rest were assigned to the States condition. Thus one-third of the total sample was allotted to each betting condition.

In Phase 2, participants assessed CEs for 105 combinations of probability and two-outcome pairs. Random participants assessed bets based on random chance odds, States condition participants assessed bets based on their answers to the US state population questions, and Football condition participants assessed bets based on their answers to the NCAA football game questions. The 105 bets were obtained by crossing the seven probability levels with all 15 two-outcome pairs that were utilized by Gonzalez and Wu (1999). These outcome combinations were (in dollars) 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. The number of two-outcome pairs was increased for this experiment in order to assess whether participants noted any changes in amount of perceived fatigue from the increased time spent on the task. Again, no bets were played out for real money, although experimenters requested that participants think through each wager as if it would be played out at face value.

Results and discussion

We removed one participant from the Football condition prior to analysis due to internal inconsistency. The form of the nonlinear mixed effects model fit to the data and on which statistical inference was based was the same as for Experiment 1. The concordance correlation coefficient for this model was 0.921. Parameter estimates and standard errors appear in Table 2.

We compared the two knowledge-based conditions, on average, with the random-based condition; if this comparison was statistically significant, we then compared the two knowledge-based conditions to each other to assess whether there was a meaningful difference between them. We used the Bonferroni correction by comparing our p values to .05/2, due to our testing multiple hypotheses in succession. In agreement with results from Experiment 1, the estimated δ value of the average of the Knowledge conditions was significantly greater than that of the Random group, (Football $= 1.553$, States $= 1.197$, Random $= 0.936$; $F(1,6913) = 6.446$, $p = .01$). There was, however, no significant difference in estimated δ values between the two Knowledge conditions ($F(1,6913) = 1.578$, $p = .21$). Also replicating Experiment 1, the difference in estimated γ values was not statistically significant between the Random condition and the average of the two Knowledge conditions (Football $= 0.657$, States $= 0.641$, Random $= 0.708$; $F(1,6913) = 0.329$, $p = .57$). All three conditions' weighting functions, with extensions to the entire probability spectrum, are depicted in Figure 5. Estimated α values were not significantly different between the average of both Knowledge participants (Football $= 0.946$, States $= 0.841$) and Random participants (0.808; $F(1,6913) = 1.085$, $p = .29$).

As in Experiment 1, significantly higher estimated δ values for the Knowledge conditions strongly suggest an overall difference in risk attractiveness when betting on events characterized by control versus random events. Knowledge participants had an elevated weighting function, indicating that risks that are characterized by control were generally seen as more attractive than equivalently risky events that one cannot control. These results appear to correspond well with the previous conclusion that betting on tasks characterized by control broadly increases risk-taking, which results from people attributing higher decision weights onto the objective probabilities of possible outcomes.

One may note the relatively smaller observed δ parameter values for the States condition of Experiment 2 ($\delta = 1.197$) compared to the Knowledge condition of Experiment 1 ($\delta = 1.492$). This difference in the magnitude of overweighting may be attributable to the inherent difference in task types; Experiment 1 participants' CEs were for answers to questions with six possible options, while Experiment 2 participants' CEs were for answers to binary questions. Observing the three weighting functions in Figure 5, it appears that

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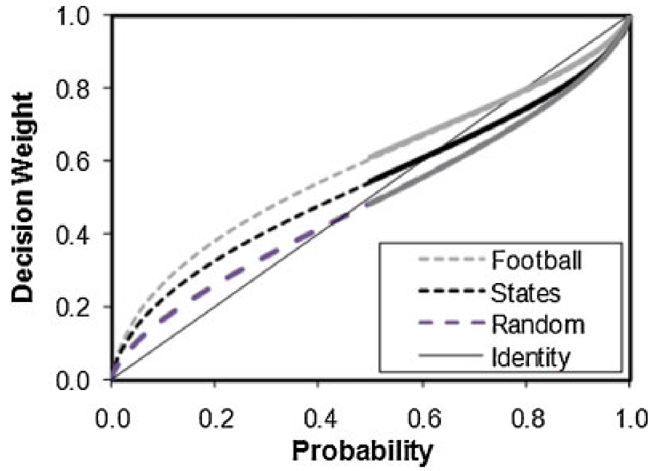

Figure 5. Weighting function curves observed in Experiment 2, within the observed range of probabilities (solid lines) and extended to the full probability spectrum (dotted lines) based on mean estimated δ and γ values

the effect of control on overall probability attractiveness may have been greater on Football questions than States questions, and we speculate that this may be attributable to the greater interest our participants felt with regard to football, which could be related to perceived control. Based on the confidence, accuracy, and overconfidence results between the two question domains (Table 3), there may be a slight trend toward increased overconfidence for football questions. However, in the absence of statistical significance, this is speculative.

We again found no significant difference in average overconfidence in answers to general knowledge questions between betting conditions (Table 3). As in Experiment 1, we observed a typical pattern of underconfidence at the lowest category and overconfidence at higher levels of confidence (see Figure 6). Interestingly, participants answering Football questions appear to be more overconfident than those answering States questions for most confidence categories.

Also, informal post-participation responses suggested that participants in Experiment 2 expressed no differences in perceived fatigue compared with those who participated in Experiment 1 as a result of the increase in bet number.

EXPERIMENT 3

In Experiment 3 we attempted to observe the effects of control on decision behavior within-subjects. Whereas Experiments 1 and 2 asked participants to respond to hypothetical bets, Experiment 3 gave participants the opportunity to play out one of their bets for real money, adding a measure of ecological validity to the design.

Method

Participants

Forty-three participants took part in Experiment 3, studied in groups of three at personal computer workstations. Participants in Experiment 3 were given the chance to play out one of their bets for real money (1/5 face value of the bet) at the end of the session.

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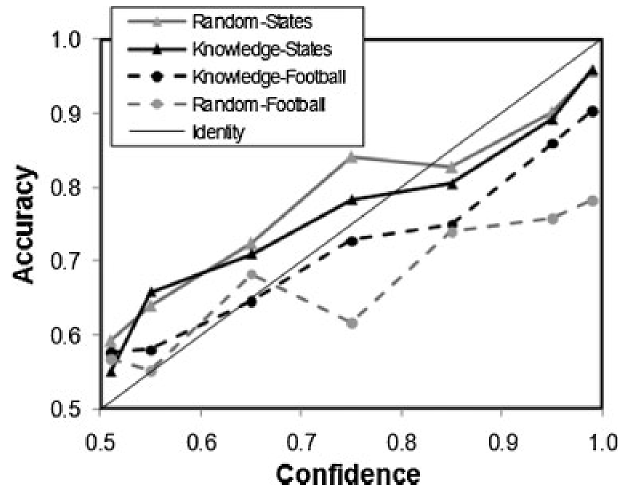

Figure 6. Confidence calibration curves observed in Experiment 2

Procedure

In Phase 1, general knowledge questions were answered, and confidence in each answer was assessed, which mirrored the general design of Experiments 1 and 2. The first question asked participants to compare the populations of two US states chosen at random, just as in Experiment 2. The second question asked participants to assess their confidence in each of their answers with one of the following categories [51, 55, 65, 75, 85, 95, and 99%]. Participants responded to 100 items in this way. Lastly, each participant was shown a few of the questions answered in each confidence category and asked to choose one that best exemplified an answer in which he/she felt the indicated degree of confidence.

In Phase 2, participants encountered two types of betting conditions: in one condition, bets were based on their answers to the US state population questions (Knowledge), while in the other condition, bets were based on random lottery odds (Random). The order of presenting the conditions was counterbalanced across participants. Participants estimated CEs for 105 bets in each condition. As in Experiment 2, all fifteen two-outcome pairs were adopted from Gonzalez and Wu (1999); thus, participants encountered up to 105 unique bets in both conditions; these unique bet combinations were the same that were used in Experiment 2. For the Knowledge condition, the outcome depended on the correctness of answers to the US state population questions. The same CE estimation process was used as in previous experiments. Participants were informed at the beginning of Phase 2 that they would have the opportunity to play out one of their bets for 1/5 of the stated value at the end of the study, but experimenters requested that all participants think through each wager as if it would be played out at full face value.

Results and discussion

We removed data from four participants prior to analysis due to internal inconsistency. The form of the nonlinear mixed effects model fit to the data and on which statistical inference was based was the same as for Experiments 1 and 2. However, because of the within-subject nature of the design, sequence effects were also included in the models for α_{ij}, γ_{ij}, and δ_{ij} to account for possible differences among subjects who received the conditions in the order AB versus BA. The presence of random subject effects in the models for Experiments 1 and 2 accounts for within-subject correlation and between-subject heterogeneity and makes the same model form appropriate for the within-subject design of Experiment 3. The concordance correlation coefficient of

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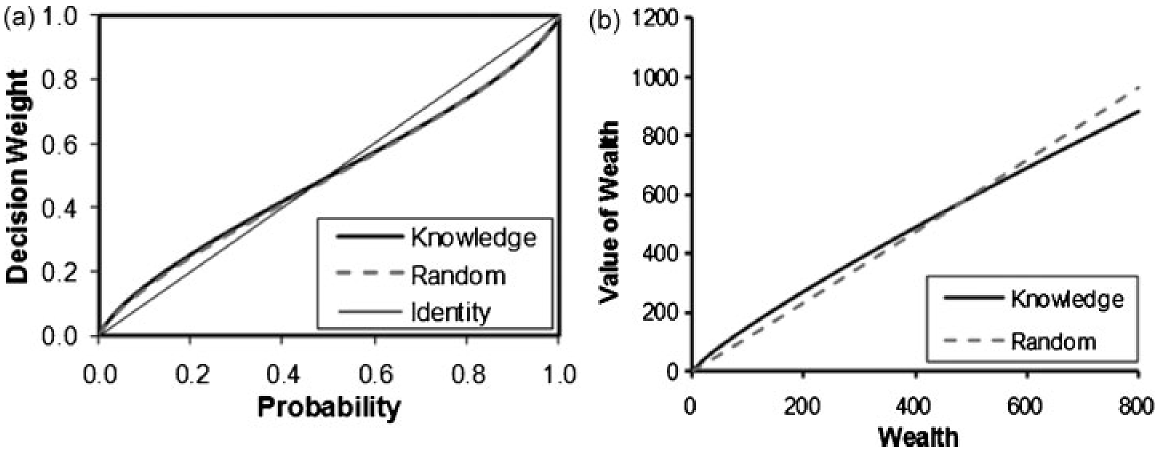

Figure 7. (a) Weighting function curves observed in Experiment 3, within the observed range of probabilities (solid line) and extended to the full probability spectrum (dotted line) based on mean estimated δ and γ values. (b) Value function curves observed in Experiment 3

the fitted model was 0.943. Again, parameter estimates and standard errors are reported in Table 2, though sequence effects, which were found to be non-significantly different from 0, are omitted for brevity's sake.

In this within-subject study, the model estimated for the Knowledge condition indicated significantly higher estimated δ values than that estimated for the Random condition (Knowledge = 0.998, Random = 0.965; $F(1,7873) = 5.741$, $p = .01$). As seen in both previous studies, estimated γ value differences were not statistically significant (Knowledge = 0.768, Random = 0.782; $F(1,7873) = 0.341$, $p = .55$). Figure 7a presents partial weighting functions utilizing γ and δ parameter estimates from both conditions, with extensions depicted from the observed probability range of [0.5,1.0] to the full range. Differences in α estimates were statistically significant between groups (Knowledge = 0.853, Random = 1.027; $F(1,7873) = 113.375$, $p < .01$); Figure 7b presents both conditions' value functions for Experiment 3.

The significant increase in δ for bets in the Knowledge condition is small but provides support in a within-subjects setting for an impact of control on the overall attractiveness of risk when betting on knowledge rather than random events. The smaller effect in Experiment 3 than in previous studies may be due to factors emerging from the within-subjects design. Fatigue, diminishing attention, and other order effects (which were incorporated in the statistical analysis, and which were not statistically significant) could have combined to diminish the magnitude of the effect that was evident after assessing up to 210 CEs (each involving making between two and six choices in the narrowing-down process), as opposed to the 72 and 105 CEs in Experiments 1 and 2, respectively. Despite the clear difficulties that are raised with a within-subjects approach to the study, the results of Experiment 3 add support for an increase in overall attractiveness of risk associated with outcomes characterized by control.

Again, a confidence calibration curve (depicted in Figure 8), reveals a typical pattern of underconfidence at the lowest category and overconfidence at higher levels of confidence.

GENERAL DISCUSSION

In three experiments we examined how decision making differs between gambles on random events and gambles with outcomes characterized by control, utilizing formal modeling within a PT framework. We

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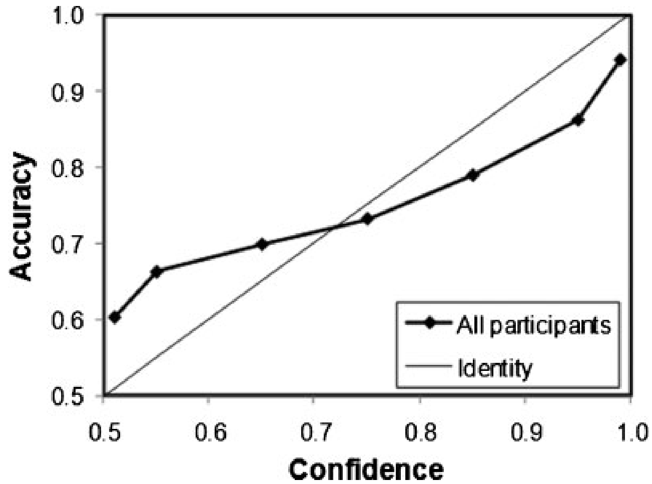

Figure 8. Confidence calibration curves observed in Experiment 3

consistently found more elevated weighting functions for participants betting on their own abilities or knowledge, suggesting significant differences in the overall attractiveness of risk between groups. In Experiment 1, this trend was pervasive across most of the probability spectrum, accounting for less-than-likely odds of success as well as more-likely odds; in Experiment 2 it was seen in participants betting both on their answers to US state population questions and questions about NCAA football games. Finally, in Experiment 3 we observed this pattern of results in participants who bet on both their answers to general knowledge questions and the occurrence of random events. These results strongly affirm previous research that purports higher risk taking for decisions in which perceived control plays a role. Further, by modeling CEs in a PT framework, this study allows for greater rigor and interpretability than had been possible before. In modeling both probability weighting functions and value functions across groups, one fundamental effect emerged consistently: those encountering bets characterized by control weighted the entire probability spectrum more highly than those encountering bets on random events. Furthermore, our results were consistent across studies in which responses were either backed by monetary incentives (Experiment 3), or not backed by incentives (Experiments 1 and 2). The results of Goodie and Fantino (1995) among others suggest that incentives make little difference, but other researchers conclude differently. Our approach exemplifies the sound approach of ‘‘do it both ways’’ (Hertwig & Ortmann, 2001).

One area in which effects of perceived control have been of especially strong interest is health psychology. Health psychology research into perceived control generally suggests that it is adaptive to individuals' mental health. Taylor and Brown's (1988) seminal article on the illusion of control and psychological well-being argued that exaggerated perceptions of control or mastery in life events are the foundations of a healthy mental state. Their work inspired a considerable body of research into whether perceived control leads to adaptive behavior (Colvin & Block, 1994). The present results shed light on the twofold nature of perceived control. In one capacity, perceived control psychologically increases various mental health states when under stress, anxiety, or pain (Taylor & Brown, 1988, 1994), which is unmistakably salutary. On the other hand, however, perceived control has a behavioral impact on risky decision making, significantly increasing the attractiveness of risk and participants' tendency to accept risk. If this extends to make individuals view risks as more attractive than the true state of events warrants, resulting decisions would necessarily be less optimal in the long run. It is also possible that this tendency serves to counteract the underweighting that prevails over most of the probability spectrum.

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The present results extend and explain our previous findings regarding the effects of control on decision making. Goodie (2003) concluded that participants accepted bets more often with tasks characterized by control. Likewise, Goodie and Young (2007) found a trend toward risk-taking in the control domain, indirectly suggesting a change in the attractiveness of probabilities. Both of these studies utilized a form of the GGT that did not allow for assessments of the subjective weighting of probabilities. The CE elicitation method provides a comprehensive representation of decision making behavior, allowing us to recognize more particular elements and characteristics of decision behavior. Within this framework, we can examine the cognitive mechanisms by which control affects decision behavior; as was found here, the weighting of probabilities was increased over the entire spectrum of probabilities. Additionally, by using the formulation of the probability weighting function formulized by Gonzalez and Wu (1999), we can progress toward a psychological interpretation of individuals' behavior by suggesting that, under conditions characterized by control, the probabilities of potential outcomes are viewed as generally more attractive.

Based on the simpler bet acceptance results found in earlier work, Goodie (2003) speculated that, under conditions of perceived control, probability weighting distributions may follow a less regressive, or even progressive, curve. Progressive probability weighting functions would evidence underweighted low objective probabilities and overweighted high objective probabilities. The present results suggest that this extreme possibility is not the case; individuals in the Knowledge conditions consistently overweighted the small probabilities and underweighted the large probabilities. However, the overall weighting of probabilities was markedly more elevated for betting on their answers than for those betting on random events. These results suggest that a generally more elevated weighting of all probabilities is associated with decisions characterized by control.

Are probability weighting and calibration curves mutually compensatory?

The weighting and calibration curves observed in the three experiments were typical of the prior literature in both being regressive. One may wonder whether these effects combine in systematic ways to produce better decisions. If low levels of confidence are in fact too low, but are buttressed by elevated weighting, might that make decisions based on relatively low subjective probabilities relatively effective? At the other end of the spectrum, if high levels of confidence are too high but are tempered by depressed decision weights, might these effects similarly combine to yield relatively effective decisions based on high subjective probabilities? We approach these questions by comparing the accuracy within each confidence category with the weight attached to that confidence category, for groups that bet on the same questions they answered (as opposed to matched random items). If these values were similar, or related to each other in a systematic way, then that relationship would constitute evidence that regressive weighting systematically compensates for regressive calibration curves. The results for all three of the present studies are depicted in Figure 9, and are not encouraging. Some points, particularly in the States condition of Experiment 2, are quite close to the identity line, but many are not. More troubling, there is no obvious relationship between accuracy associated with a particular level of confidence, and weighting of that level of confidence. In Experiment 2, the curves are defensibly linear, but risk seeking in one group and risk averse in the other. There is a clear regressive curve in Experiment 1, but an equally clear progressive curve in Experiment 3. We conclude that the present results do not include systematic evidence of a compensatory relationship between the regressive calibration and weighting functions.

Contextual effects

One could also speculate that category and range effects may have a differential effect on the shape of the probability weighting function between experiments. Relating Parducci's (1973, 1983) range–frequency theory to the present work, estimations of confidence in answers to general knowledge questions may differ

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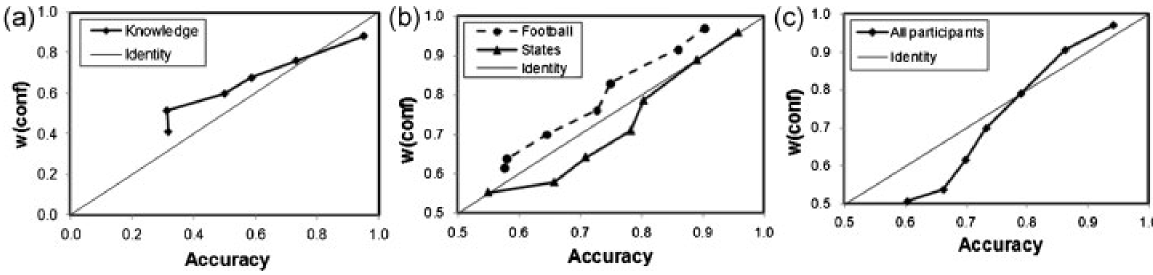

Figure 9. Curves relating accuracy within confidence categories to weighting of confidence categories, in groups that bet on the same items they assessed confidence in, for (a) Experiment 1, (b) Experiment 2, and (c) Experiment 3. A unity function would reflect a compensatory relationship between the two

between a six-option choice (Experiment 1) and a two-option choice (Experiment 2). In all three studies, Knowledge participants ultimately assessed bets related to general knowledge questions that they perceived as being related to one of either six confidence categories (Experiment 1) or seven confidence categories (Experiments 2 and 3). We argue that this difference in the number of confidence category options does not vary as widely as those discussed by Parducci (1973, 1983), who was interested in much larger differences between category numbers—for example, between 3 and 9 categories.

Similarly, the ranges between confidence categories were specifically chosen to be similar within experiments (Experiment 1 ranges = 0.15; Experiments 2 and 3 ranges = 0.05–0.10). As such, significant range effects may not be expected between the present experimental designs. However, the probability ranges across experiments could not match exactly due to the ostensible difference in confidence in answers between question types. Subsequently, the six-option forced choice question format in Experiment 1 requires a larger range between confidence categories (range = 0.15) than the binary forced-choice format in Experiments 2 and 3, which varied in confidence category range between 0.05 and 0.10. Range effects may, in fact, partially explain why we see higher overall δ parameter values for Experiment 1 than the other two experiments, although this is speculative.

Limitations and future directions

There are some limitations to the results found with the present research. It is possible that explicit estimations of confidence in their answers and intuitive judgments of confidence may not correspond, as is suggested in dual-process models of cognitive processes (Kahneman & Frederick, 2002). Kahneman and Frederick note that the boundary between the automatic system of perception and the more reflective system of overt judgment is fuzzy, and a decision maker relies on the reflective system to correct for potential errors in the intuitive system. Although the current study does not attempt to directly partition the influences of either cognitive system, future studies may investigate the distinct effects of the intuitive and reflective systems that account for judgments of confidence; we postulate that this may be accomplished by comparing confidence estimates within a time-stressed environment—which would not allow for the reflective system to assist in confidence estimation—with confidence estimates in an environment with no deadlines.

Additionally, the present studies apply only to uncertain contexts in which the true probabilities could be known but are unknown. There is an important distinction between uncertain events that are unknown and uncertain events that are unknowable (Chow & Sarin, 2002). Unknowable events share the characteristic that important information regarding the prospect is unavailable for everyone; examples of unknowable events include the outcomes of future sporting events. Future research could examine the differences between the effect of control on both unknown events (as examined in the present case) and unknowable events.

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Finally, it would be interesting to examine relationships between perceived control as a situational variable (as demonstrated here) and perceived control as stable personality trait. For instance, social psychologists have shown interest in various personality traits that tap into an individual's need to feel in control of the occurrence of events (e.g., Langer, 1975); those who rate high in controllability have been found to accept risk differently that those who rate low in controllability. Similarly, an individual may feel more perceived control for one domain than another. In the present context, a football statistics expert may feel a greater sense of perceived control over the Football bets of Experiment 2 than the States bets. Work done along this vein has been positive (Heath & Tversky, 1991). Future research should continue to investigate the relationship between personality and situational variables on decision making, which would build on the finding that perceived control increases risk attractiveness.

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