Predicting Risk-Sensitivity in Humans and Lower Animals:

Risk as Variance or Coefficient of Variation

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Abstract

In this paper, we examine the determinants of risk-sensitivity exhibited by humans and other animals. Our dependent measure is the proportion of respondents who choose a sure option over a risky option with equal expected value. We present a meta-analysis of human risk-preference data and compare it to the results of a similar meta-analysis of animal data by Shafir (2000). Both sets of data show that the coefficient of variation (CV), a relative measure of risk per unit of return, significantly predicts choices across a broad range of decision situations. In those situations where the CV can be compared to outcome variance, a more traditional (absolute) measure of risk, the CV outperforms variance as a predictor of risk sensitivity. This is especially true when decision makers (humans, or animals foraging for food) acquire information about choice outcomes and their variability experientially and over time, as demonstrated in an experiment in which we attempted to put students into a risky learning and decision making situation comparable to the experiential information acquisition in risky foraging choice tasks in animal experiments.

Decision making under risk and uncertainty is a topic of research in disciplines as diverse as psychology, economics, zoology, and entomology. Both the animal and the human risky choice literatures have proposed models that either predict choices in a deterministic fashion or predict risk sensitivity (i.e., the probability of choosing a riskier or less risky option) in a stochastic fashion. Theories of human risky choice include the prescriptive expected utility model (von Neuman & Morgenstern, 1947) or the risk-return models used to price risky options in finance (Markowitz, 1959). A prominent descriptive model is prospect theory (Kahneman & Tversky, 1979). In the animal literature, theories about risky foraging gave rise to the energy budget rule (Caraco, 1980, Stephens, 1981), a special case of a general class of normative models called risk-sensitivity theories (RST) that construe risk-sensitivity as the response of organisms whose goal is the maximization of Darwinian fitness in stochastic environments. Similar to prospect theory for human risky choice, the energy budget rule predicts risk aversion when animals are not in danger of starvation (domain of gains), but risk-seeking when there is such a risk (domain of losses). The *American Zoologist* recently devoted a special issue (Vol. 36, 1996) to the topic of risky animal decision making in situations ranging from foraging to habitat selection and reproductive choice.

While different in many respects, these models all assume that the likelihood of choosing a risky option is, ceteris paribus, affected by the variability of the option's possible outcomes. The measure of variability used in these models is usually the variance of outcomes around the option's expected value. The capital-asset-pricing model in finance, for example, equates risk with variance and predicts that people's willingness-to-pay for risky options with equal expected value is a decreasing function of the options' outcome variance (Sharpe, 1964). The energy budget rule, as another example, predicts that—among options with equal expected energy intake—animals will prefer foraging options with smaller variance when the expected energy intake exceeds the caloric needs of the animal, but will prefer options with greater variance when the expected energy intake is less than that required for survival.

However, observed levels of risk-sensitivity for humans as well as other animals often deviate from the predictions of these models (see Kacelnik & Bateson, 1996, and Shafir, Wiegman, Smith, & Real, 1999). Human risky choice data (e.g., Weber, 1988; Weber & Milliman, 1997) suggest that the predictive shortcoming of these models probably stems from their use of outcome variance (or standard deviation) as a measure of risk. Variance seems to be the wrong measure of risk for some reasons that have been discussed elsewhere (Luce & Weber, 1985).[1] In this paper we address an additional shortcoming of outcome variance (or standard deviation) as a measure of risk that relates to the fact that people (and other animals) may perceive and encode outcome variability not in an absolute fashion, but relative to the average level of outcomes. Like Weber (1999; Weber & Hsee, 1999) in a different context, we argue that characteristics of the subjective *perception* of variability or risk need to be considered to arrive at accurate predictions or interpretations of behavior in risky choice situations.

To make this point we take a brief detour into psychophysics. Psychophysical investigations of people's judgments of simple sensory continua (e.g., loudness, brightness) show that the difference in stimulus magnitude required to see two stimuli as different grows in proportion to the stimulus to which the difference is added (Weber, 1834). This difference (called "just noticeable difference" or JND) provides a measure of discriminability in psychophysical judgments. Weber's law describes the fact that the JND grows in direct proportion to the absolute level of stimulus magnitude. Savage (1954, p. 103) applied the logic of Weber's law to the evaluation of outcome differences in the context of riskless choice, describing a regularity in people's subjective evaluation of outcomes subsequently called percentage-framing (Thaler, 1980), where a difference in outcome values is judged proportionately to the magnitude of the reference outcome. Thus a $100 price reduction seems significant when buying a $200 pen (a saving of $100/$200 or 50%), but trivial when buying a $20,000 car (a saving of only $100/$20,000 or half a percent). In combination, these results suggest that the coefficient of variation (CV), a measure of the *relative* variability of risky choice alternatives that is calculated by dividing the standard deviation of outcomes by their mean, might be a better predictor of risk sensitivity than the unstandardized variance (or standard deviation).

The CV is, indeed, widely used as a measure of relative risk (or measure of risk per unit of expected returns) in applications that include engineering (e.g., Abacus Technology Corporation, 1996), medicine (e.g., Dartmouth Atlas of Healthcare in Michigan, 2000), agricultural economics (e.g., Johnson, Williams, Gwin, & Mikesell, 1986), and financial management (Gunther & Robinson, 1999; Rajgopal & Shevlin, 2000). Aside from greater psychophysical plausibility as a measure of perceived variability or risk, the CV has the advantage of allowing comparisons of risk sensitivity across choice situations that differ in range (e.g., the weight of mice vs. the weight of men) or outcome dimension (e.g., weight vs. height). Dividing the standard deviation by expected value makes the CV dimensionless, an advantage for comparative analyses that has not gone unnoticed by methodologists in ecology or other applied research areas (Hilborn & Mangel, 1997).[2] It is precisely the possible cancellation of measurement units in the numerator and denominator that makes the CV a more attractive standardization of perceived variability or risk than the division of variance by EV.

Of bees and men: The utility of cross-species comparisons of risk taking

The animal literature on risky decision making, including risk-sensitive foraging, is bound to hold lessons for human decision making under risk and uncertainty. Human responses to risky situations derive, at least in part, from the same mechanisms evolved by other animals in response to the stochasticity of their natural environment. In addition to learning on an evolutionary scale, learning on an ontogenetic scale is involved in shaping the behavior of both humans and other animals in risky environments (Thorndike, 1898; Williams, 1988). However mediated, many similarities in the decision behavior of humans and other animals have been documented, including matching rather than maximization behavior (e.g., Commons, Herrnstein, & Rachlin, 1982) and violations of the postulates of the EU model, in particular intransitivity of preferences (Shafir, 1994) and the Allais paradox (for a review see Real, 1996).

In this paper, we take a two-pronged approach towards examining the similarities and differences in risk-sensitivity exhibited by humans and other animals. First, we compare the results of a meta-analysis of human risk-preference data to the results of a similar meta-analysis of animal data by Shafir (2000), who found that the CV was a better predictor of risk-sensitivity than variance. Secondly, we report the results of an experiment in which we attempted to put humans (undergraduates at the Ohio State University) into a risky learning and decision making situation comparable in important aspects to the risky foraging choice tasks in animal experiments.

Some Caveats

The models discussed in this paper (including the suggested modifications) all merely aspire to predict risky choice. The goal of models such as the EU model of human risky choice or the energy budget model of animal foraging is to predict choice behavior as a function of general characteristics of the outcomes of the choice alternatives. They are moot on the processes by which hypothesized choice regularities may arise. The main argument of our paper is that variability of outcomes is a *relative* concept and that its relative nature is best captured by standardizing the standard deviation of outcomes by dividing by the alternative's expected value. We show that the resulting measure, the coefficient of variation (CV), is a better predictor of risk sensitivity than either the standard deviation or the expected value alone (or in combination), without making any assumptions about the processes that would give rise to this regularity.

This is not to say that such process models do not exist. Kacelnik and collaborators have recently provided process model candidates that account for observed regularities in the risk sensitivity of songbirds and other foragers as a function of variability in outcome amounts as well as outcome delays (Kacelnik & Bateson, 1997; Kacelnik & Brito e Abreu, 1998; Reboreda & Kacelnik, 1991). In these models, Weber's law influences the decision process by either affecting outcome evaluation or memory retrieval.

Our emphasis on the relative nature of risk perception in this paper also neither addresses nor invalidates other concerns about variance as a measure of risk (Luce & Weber, 1985). Future studies with more complex risky choice options than two-outcome lotteries should look, for example, at a possible asymmetry in the effect of the upside CV vs. downside CV, i.e., compute the positive and negative semi standard-deviation of choice alternatives and standardize each by the options' EV. [3]

Finally, our postulate that the CV is a better predictor of risk sensitivity than variance does not question in any way that many other variables other than outcome variability affect risk sensitivity. Some of those related to human decision making are further discussed below. In the animal literature, other variables include species differences in social organization and/or resource utilization that affect the animals' utility for outcomes differing in volume, concentration, or delay (see Kacelnik & Bateson, 1996, 1998). Such variables can be expected to reduce the fit of models that predict risk sensitivity simply as a function of CV.

Empirical Evidence for CV vs. Variance as Predictor of Risk Sensitivity

Meta-Analysis of Animal Data

Shafir (2000) demonstrated that predictions of risk-sensitivity for a wide range of animal foraging data are much improved by the use of the CV rather than the variance or standard deviation of outcomes as a predictor variable. Shafir's meta-analysis included the studies reviewed in Kacelnik & Bateson (1996) as well as four more recent studies. Some studies consisted of a single experiment; other studies consisted of several experiments. In each experiment, foraging animals (wasps, bees, fish, and songbirds) had to choose between an option that provided a constant reward and an option that provided a variable reward with an expected value equal to the constant reward. Food rewards included sucrose solution of varying concentrations, seed pellets, and mealworms). In all cases, animals learned about the reward distribution offered by the two choice alternatives by repeated exposures prior to the experimental choice trials. The dependent measure was the proportion of choice trials for which animals chose the alternative with the constant reward.[4] In 8 of these experiments, the energy budget was negative. In the remaining 49 experiments, the energy budget was positive.

As mentioned above, use of the CV rather than variance or standard deviation as the predictor of risk sensitivity makes it possible to include experiments with different types of reward units in the same analysis. Dividing the standard deviation by expected value makes the CV dimensionless. Thus Shafir was able to include different species of foragers (nectarivores and non-nectarivores) and types of reward (nectar differing in volume or concentration or solid food rewards such as seeds or mealworms differing in number) in his meta-analysis.

Since the expected value of rewards was the same within each pair of choice options, risk—return models of choice (including the energy budget rule) would predict that relative preference for the constant reward option is a function of the variability of the variable reward option. More formally, the utility of a risky option X, E[u(X)], can be expressed as a tradeoff between the utility of an option's expected value (EV) and its risk (R) (Bell, 1995):

$$E[u(X)] = u[EV(X)] – b\,R(X). \qquad (1)$$

For a quadratic utility function, R(X) is equal to the variance. Other utility functions are consistent with other measures of risk (Bell, 1995; Jia & Dyer, 1997). Regardless of the measure of risk, the difference in utility between risky option X and sure option Y that is equal to the expected value of X will be:

$$E[u(Y)] – E[u(X)]= u[EV(X)] – [u[EV(X)] - b\,R(X)] = b\,R(X) \qquad (2)$$

Thus, if preference for sure option Y (and thus the proportion of respondents choosing the sure thing, p(ST)) is proportionate to the difference in utility between choice options, then p(ST) should be an increasing linear function of the riskiness of option X, R(X).[5] A similar result holds if we assume an exponential version of Luce's (1959) probabilistic response rule, which is commonly used in adaptive learning research (e.g., Camerer & Ho, 1999):

$$p(Y,X) = \frac{e^{E[u(Y)]}}{e^{E[u(Y)]} + e^{E[u(X)]}} = \frac{e^{u[EV(X)]}}{e^{u[EV(X)]} + e^{u[EV(X)]-bR(X)}} =$$

$$\frac{e^{u[EV(X)]} / e^{u[EV(X)]}}{(e^{u[EV(X)]} / e^{u[EV(X)]}) + (e^{u[EV(X)]-bR(X)} / e^{u[EV(X)]})} = \frac{1}{1 + e^{-bR(X)}} \qquad (3)$$

In this case, p(ST) is an increasing logistic function of the riskiness of option X, R(X), that can be approximated reasonable well by a linear relationship for intermediate ranges of X.

To test whether the dimensionless CV as a measure of perceived risk (R(X)) predicts strength of preference for sure option Y, Shafir (2000) regressed the proportion of choices favoring the constant reward alternative (p(ST)) on the CV, separately for both positive and negative energy budget experiments. As shown in Figure 1, for positive energy budgets larger variability (CV) was associated with greater risk-aversion: p(ST) = 0.53 + 0.001 CV, $F_{1,48} = 22.13$; $R^2 = 0.33$, $p<.0001$. For negative energy budgets, larger variability (CV) was associated with greater risk-seeking: p(ST) = 0.52 - 0.0012 CV, $F_{1,7} = 5.08$, $R^2 = 0.42$, $p<.1$. In light of the wide range of species and types of reward included in the regressions (which can all be expected to affect risk sensitivity in addition to CV), these fits are impressive.

Shafir (2000) also addressed the question whether risk preference is only sensitive to outcome variability in experiments with risky options that involve zero outcomes, a point of contention in the animal literature where some studies have reported such a difference in results (between risky choices that involve zero outcomes and those that do not) and other studies find risk sensitivity in both kinds of experiments. To test for an effect of zero- vs. non-zero-outcomes, Shafir combined both positive and negative energy budget experiments and computed risk sensitivity as deviations of p(ST) from .5. An ANOVA of this measure of risk sensitivity showed no main effect for zero-outcomes ($F_{1,53} = 2.12$, $p>.10$). The apparent effect of zero vs. non-zero outcome in some studies is most likely an artifact of the fact that studied zero-outcome choice options happen to have greater CVs (as shown in Figure 1) and that greater CVs result in greater risk sensitivity.

The advantage of using the CV as a predictor of risk-sensitivity is that it allows for the inclusion of a large number of relatively heterogeneous studies. The downside of using a disparate set of studies is that the relative ability of CV to predict choice proportions cannot be compared with that of other possible predictors such as the variance, standard deviation, or expected value of the outcomes of the variable award, because these predictors are not comparable across studies that do not use the same type of outcomes. We can provide this information, however, for a subset of experiments analyzed by Shafir (2000), which used the same type of respondent and reward. Choice proportions came from bees and wasps, and variability was in the volume of the reward, which was nectar of a particular concentration.

As shown in Figure 2, the CV accounted for a large proportion of the variation in risk-sensitivity ($|p(ST) - .5| = -0.05 + 0.0015$ CV, $F_{1,10} = 25.0$, $R^2 = 0.71$, $p<.0005$), while the standard deviation ($F_{1,10} = 0.00$, $R^2 = 0$, NS) and variance ($F_{1,10} = 0.13$, $R^2 = 0.01$, NS) did not. To examine the possibility that risk sensitivity is a function of the magnitude of the stakes (i.e., the expected value of the pair of choice alternatives) and that the CV is a better predictor of risk sensitivity because it incorporates the EV in its denominator, we regressed risk sensitivity on EV. As shown in Figure 3, mean nectar volume did not predict risk sensitivity ($F_{1,10} = 0.43$, $R^2 = .04$, NS). In summary, neither standard deviation nor EV predict risk sensitivity in isolation. Their ratio, however, in the form of the CV does so very well.

Meta-Analysis of Human Data

To test the ability of the CV to predict risk sensitivity in human respondents, we searched the literature on human risky choice for choice pairs that were similar in structure to the animal choice situations analyzed by Shafir (2000). A comprehensive search identified the 18 studies listed in Table 1 that provided a total of 204 choice situations with the following characteristics. Each situation presented a choice between either two gain options or two loss options. In all cases, one of the options assured a certain outcome; the other alternative had two potential outcomes that occurred probabilistically. The expected value of both alternatives was the same within a given pair. For each choice pair, the published record provided the proportion of respondents (out of the study's sample size, n) who chose the sure thing (p(ST)), as well as coding information about other variables, as shown in Table 1: respondents' gender, age category (young adults, older adults, or mixed), and nationality (American, Israeli, Chinese, Japanese, British, or Dutch), the substantive domain of the decision (money, time, human lives, etc.), the sign of the decision outcomes (gains vs. losses), whether one of the two uncertain outcomes was a zero outcome, whether respondents had received advance payments, and whether the choice was hypothetical or had real consequences.

We regressed p(ST), the proportion of respondents who selected the sure-thing choice alternative, on the list of predictor variables in Table 1.[5] In addition to these qualitative predictors, we used the following two quantitative variables as predictors of risk preference: the CV of outcomes in the risky choice alternative as a measure of relative risk and the probability of the lower of the two possible outcomes of the risky choice alternative (and its interaction with CV) as a measure of outcome skewness, a proxy for the possibly asymmetric effect of upside vs. downside variability on risk perception and thus risk sensitivity. Since both of these predictors are dimensionless, we could examine their effect across a broad range of choice situation, combining choices in all substantive outcome domains into a single analysis. A preliminary analysis confirmed the prediction of prospect theory (Kahneman & Tversky, 1979) that risk sensitivity (i.e., sign and magnitude of deviation of p(ST) from .5) depends more on relative outcome framing (relative gain vs. relative loss: $F_{1,201} = 64.13$, $p<.0001$) than absolute outcome value (absolute gain vs. absolute loss: $F_{1,201} = 26.82$, $p<.0001$).[5] We conducted two separate regressions for gain and for loss framed choice situations and examined the effect of the absolute sign of outcomes (absolute gains vs. absolute losses) within each analysis.

The results are shown in Table 2. For choices between gains, the set of predictor variables accounted for 62 percent of the variance in p(ST). For choices between losses, the regression accounted for 53 percent of the variance. Tables 2 and 3 show F-values and significance levels for two different sums of squares (SS). Type I SS assess the marginal contribution made by a given predictors given that the previously listed variables are in the regression equation. Type III SS assess the marginal contribution of the predictor given that *all* other listed variables are in the regression equation. Unless otherwise specified, it is the significance of the Type III SS that is discussed below.

The most important result for the purposes of this paper is that the coefficient of variation was a significant predictor of risk taking in both the gain and the loss domain. In the domain of gains, a larger CV was associated with a greater probability to choose the sure option. The effect went into the opposite direction in the domain of losses, where a larger CV was associated with a smaller probability to choose the sure thing. The absolute sign of outcomes mattered for gain-framed options but not for loss-framed options. Risk aversion was stronger when outcomes that were framed as a gain really were gains in an absolute sense, rather than being reduced losses.

The gender of respondents did not affect choice significantly, partly because of a lack of variation in the predictor variable. As shown in Table 1, few investigators report choice behavior separately as a function of respondents' gender. Age affected choices in the loss domain before controlling for other variables, with older adults being more risk-seeking than younger adults. Nationality of respondents affected choices in the loss domain and marginally in the gain domain, after controlling for differences on other variables between choice situations from different countries. Americans (who constituted the vast majority of respondents) were less risk-seeking (for losses) or more risk-averse (for gains) than the small number of respondents of other nationalities (Japanese, Dutch, British, and Chinese).

Similar to the animal data, the presence of a zero-outcome did not affect p(ST) for either gain or loss choices. The skewness of the risky option (p(low outcome)) affected risk taking to a very sizable degree for gain choices and the interaction of p(low outcome) with CV was significant for both gains and loss choices. The nature of the interaction was consistent with the hypothesis that risk perception is more sensitive to downside rather than upside variability.

Whether choices were purely hypothetical or involved real payoffs had a significant effect for both gains and losses, with real payoffs resulting in greater risk aversion for choices involving real gains and less risk seeking for choices involving real losses. Receiving an upfront payment before making a (financially)[7] risky decision had a significant effect only on choices involving losses, where it made respondents more risk seeking, consistent with Thaler and Johnson's (1990) house-money effect.

The substantive domain of the decision (e.g., gambling for money vs. for human lives) had a marginally significant effect on risk taking for choices in the gain domain (where choices involving gains in human lives were less risk averse than choices involving other outcome dimensions) and a highly significant effect in the loss domain (where choices between options involving the loss of human lives were more risk seeking).

To compare the ability of the EV, standard deviation, variance, and CV of the risky choice alternatives to predict risk sensitivity (following Shafir's (2000) lead), we restricted our regression analyses to choices between monetary outcomes where we were not restricted to dimensionless quantitative predictors. The results are shown in Figure 3, again separately for choices between gains and choices between losses.

In the gain domain, both EV and CV were significant predictors of risk taking, accounting for 62% of the variance in conjunction with the other predictor variables. Using the same set of predictors in combination with either the variance or standard deviation of outcomes (instead of the CV) reduced the proportion of variance accounted for to 58 or 59%. In the loss domain, the corresponding proportion of variance accounted for was 62% for the regression involving the CV, and 59% and 56% for the regression involving either the variance or standard deviation, respectively. Furthermore, neither standard deviation nor variance were significant predictors of risk sensitivity for either gain or loss choices, whereas the CV almost reached levels of marginal significance.

Whether outcomes were hypothetical vs. real affected risk sensitivity for both gain and especially loss choices, as did the presence of a zero outcome in the risky choice alternative. Real financial outcomes made respondents more risk averse for gains and less risk-seeking for losses, whereas the presence of a zero-outcome increased risk aversion for gains and risk seeking for losses.

In summary, our meta-analysis of existing human risky choices showed that the coefficient of variation may be a more useful predictor of risk taking than other measures of variability or risk for human respondents. In addition to the CV, other variables also predicted risk taking, including the EV of the choice pairs for choices between financial gains, and outcome skewness for gain lotteries, indicating an asymmetric effect of upside and downside variability on perceived risk.

The results implicating the CV as a predictor of human risk sensitivity were not as compelling, however, as those of the animal data. To test a potential reason for this discrepancy, we conducted the following experiment.

Cardgame Experiment

Learning outcome value and probability by experience

In this study, we tried to recreate as closely as possible the learning conditions of typical animal risky foraging decision making studies. Without the benefit of symbolic representations, nonhuman animals need to acquire information about the likelihood and quality of outcomes in different choice alternatives through repeated sampling and personal experience. It is possible that psychophysical effects like Weber's law (i.e., reference-point relative encoding of outcome variability) are more pronounced in situations where outcome information is acquired by personal experience over time than in the typical choice situation studied in judgment and decision making research where outcome magnitude and their probabilities are communicated symbolically (mostly numerically or in a visually analogue fashion). All studies included in the meta-analysis in the human data presented choice alternatives in a summarized, symbolic fashion, using either a numeric format (e.g., ($20, .1; $0, .9) vs. $2 for sure) or a spinner wheel or bar chart that showed the probability and outcome information for each alternative. We hypothesized that the advantage of the CV over variance as a predictor of human risk sensitivity would be stronger in situations where human respondents acquire information about risky choice options experientially.

Undergraduate students at the Ohio State University came to an experiment on risky decision making that advertised that participants could win money as a function of their decisions and preferences. Each of the 110 participants went through the following sequence of events in a one-on-one session with an experimenter. The experimenter presented them with two decks of cards, each deck consisting of 50 cards. The deck to their left was labeled L, the one to their right was labeled R. Respondents were told that they had the opportunity to sample cards from the two decks, in any order they desired, until they had a good idea which of the two decks was "better," in the sense that they would prefer to draw from it for a trial involving a real monetary payoff. Any card that was turned over revealed a money amount that would be won as the result of drawing the card. Respondents sampled at their leisure, drawing on average about 20 cards from each deck, without replacements. At the end of this sampling period, respondents indicated to the experimenter from which deck (L or R) they preferred to draw a card for the real-payoff trial. Unbeknownst to the respondents, the cards in one of the two decks all had the same positive payoff ($x), whereas the cards in the other deck provided two different payoffs, one zero ($0) and the other a larger positive payoff ($y, y>x). Both decks had equal expected payoffs. Respondents received no information about outcome magnitudes or probabilities other than what they obtained by sampling cards from the two decks.

The experimenter shuffled the deck that was chosen by the respondent, who then drew a card at random. The obtained payoff was noted before the respondent moved on to a new set of two decks for which the sampling and decision procedure was repeated. Each respondent indicated their preferred deck from five pairs of decks, respectively, in this way, drew a card from each of the preferred decks, and finally rolled a die that determined for which of the five obtained outcomes he or she would receive an actual monetary payoff.[7] The possible outcomes, their probabilities, and expected values of the five choice pairs are shown in Table 4. The position of the constant payoff deck as the L or R deck was counterbalanced across pairs and respondents.

As can be seen in Table 4, the five choice pairs included in the study were selected in such a way that the variable payoff decks of three of the choice pairs were equal in variance but differed in CV, whereas another set of three were equal in CV but differed in variance. Just as in the meta-analyses reported above, both choice alternatives (the two decks) had equal EV, leading again to the prediction that the proportion of respondents choosing the constant payoff deck (p(ST)) should be a (positive) linear or perhaps logistic function of the perceived riskiness of the variable-payoff deck. Our design allowed us to see very clearly whether variance or CV is a better measure of perceived risk in the sense of better predicting differences in risk sensitivity and choice.

Visual inspection and statistical analysis of the choice proportions shown in Table 4 confirm our prediction that risk-aversion increases with the CV ($r = .84$, $p<.10$) rather than with the variance of outcomes ($r = -.22$, NS). Just as for the monetary gain decisions in the meta-analysis, EV of the options of the choice pair also affected the likelihood of choosing the sure thing, in the direction that respondents were less risk-averse for greater EV ($r = -.90$, $p<.05$). However, the CV predicts choice proportions even when EV is in the regression equation, with an increase in R^2 from .80 to .91. Variance, on the other hand does not predict choice proportions, either by itself or on the margin of EV.

Role of Learning from Feedback

March (1996) recently provided an experiential learning interpretation of risk preference for situations that closely parallel the conditions of the cardgame experiment. The learning models that he applied to risky choice situations in a set of simulations were classic and simple reinforcement learning rules (dating back to the 1960s) that assume that people change their propensity to choose the sure option from initial indifference (.5) as the function of the feedback they receive from the options they chose on previous trials. The use of simple learning rules to predict behavior in uncertain environments, has also been of interest in the animal literature (Hammer & Menzel, 1995; Montague, Dayan, Person, & Sejnowski, 1995).

For the set of choice pairs used in the Cardgame experiment, we simulated the choice propensity for the sure thing of respondents who would follow two of the learning models resurrected by March. Both the fractional adjustment model (a variation on the classic Bush-Mosteller (1955) and Estes (1959) stochastic learning model) and the weighted return model (a variation on exponential updating) yielded predictions (assuming 20 learning trials, the average number of cards sampled by our respondents) that correlated far more highly with the CV of the five choice pairs (between .83 and .99 for the two models across a range of parameter values) than with the variance (between -.08 and .46 for the same models).

Correlations between model predictions and observed choice proportions were also high, and significantly higher for the weighted return models (around .90) than for the fractional adjustment models (around .60). The predictions shown in Table 4 come from the weighted return model

$$\text{Utility}(\text{Option}_i, t+1) = a\ \text{Outcome}(\text{Option}_i, t) + (1-a)\ \text{Utility}(\text{Option}_i, t), \qquad (4)$$

and

$$p(\text{Option}_i, t) = \text{Utility}(\text{Option}_i, t) / (\text{Utility}(\text{Option}_i, t) + \text{Utility}(\text{Option}_j, t)) \qquad (5)$$

with a value of a = 0.2. In this model, the probability of choosing an option changes on the basis of the history of returns of both alternatives. Respondents update their impression of the utility of a choice option after each choice of that option by computing a weighted average of their previous impression and their most recent outcome experience. The learning parameter a determines the weight given to recent over more remote experiences. The probability of choosing option i in period t is determined by Luce's choice rule (1959), i.e., is proportional to the relative strength of option i's utility (the ratio of its utility over the sum of all options' utility). The shown model predictions have a correlation of .91 with the observed choice proportions (even if they overpredict the general level of risk-aversion) and a correlation of .99 with the risky options' CV.

It should be noted that cumulative prospect theory (Tversky & Kahneman, 1991) does not predict the observed choice proportions. Coding predictions of risk-seeking (choice of gamble) as 0 and risk-aversion (choice of ST) as 1, prospect theory predictions have a correlation of -.71 with the observed choice proportions. Predicting strength of preference using Luce's choice axiom applied to prospect theory valuations of the choice options results in a correlation of -.60 between predicted and observed choice proportions.

Other theories that treat risky choice as a dynamic and stochastic process, on the other hand, make predictions that do correlate with observed choice proportions. Decision field theory (Busemeyer & Townsend, 1993), for example predicts choice proportions (also shown in Table 4) that have a correlation of .95 with observed choice proportions. Similar to the learning models described above, its predictions correlate with the risky options' CV (r = .69) but not with their variance (r = -.16). Decision field theory has its roots in early motivational models of approach—avoidance conflict and models the choice deliberation process as an accumulation of information about the consequences of a decision over time (where consequences can either be experienced in real time, as in the sampling of cards in our experiment, or by sampling from memory).

Summary and Conclusions

The animal and human data presented in this paper suggest that risk sensitivity of human respondents as well as that of lower animals share common characteristics. Both seem to be better predicted by the coefficient of variation than by the variance or standard deviation of risky choice alternatives. The coefficient of variation is a standardized measure of risk that expresses variability of outcomes relative to expected returns. Introspection suggests that such standardization has face validity. A lottery with a standard deviation of $100 seems riskier when the lottery's EV is $500 than when it is $5 million.

Dynamic learning and choice models that assume that risk sensitivity is shaped by decision outcome feedback over repeated trials make predictions for the choice situations studied in the cardgame experiment that are consistent with the CV (rather than variance) of the risky option as a predictor of risk sensitivity. This appears to be true for a range of models that differ in their assumptions about the evaluation of choice alternatives and the (probabilistic) response rule. The necessary and sufficient conditions for models to predict choice proportions that covary with the risky options' CV (rather than its variance) remain to be specified.

Our results can also be related to the risk—return models discussed earlier in the paper. It is easy to show that there exists no utility function such that the expected utility of a lottery X can be expressed as a risk—return model with a simple expectation as a measure of return and the CV(X) as a measure of risk, along the lines spelled out by Bell (1995) and Jia & Dyer (1995). In these models, the outcomes of risky option X are standardized by subtracting the option's mean: R(X) = f [E(X – EV(X)]. What our paper suggests is that a more appropriate standardization might by *dividing* outcomes by the option's mean. Dyer and Jia (1997) show that such models that do so (which they call relative risk—value models[9]) can explain many empirical choice patterns unexplained by EU theory and thus labeled paradoxes. Our results suggest that existing deviations of human choice behavior from prescriptive models in finance and economics should be examined in light of the fact that people are responding to a different index of risk than that assumed to underlie their choices in those models and that a ratio model (rather than a difference model) expresses people's comparison and evaluation of possible outcomes.

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Footnotes

1 One important problem is the fact that variance treats deviations above and below the mean symmetrically even though most people are vastly more concerned with downside variability than upside variability when judging risk (e.g., Bontempo, Bottom, & Weber, 1997).

2 One drawback of the CV is that it is undefined for risky options that have an EV of zero. This is not a problem for the risky options described in this paper that have outcomes either in the domain of gains (with EVs greater than zero) or in the domain of losses (with EVs less than zero).

3 The results of our meta-analysis of human choice data reported below suggest that such additional refinements will be necessary.

4 In our analysis of the animal and the human data, the implicit assumption is that respondents are homogeneous, which allows us to aggregate across respondents and to analyze group choice proportions as the dependent measure.

5 It is, of course, possible that the degree of risk sensitivity, expressed by coefficient b, depends on other variables, including the EV of the choice options (as hypothesized by Dyer and Jia, 1997). We test this possibility below for both the animal and the human data.

6 Since the dependent variable was a (choice) proportion, we applied an arcsine-transformation to it in this and all other analyses to guard against homoscedasticity assumption violations.

7 Upfront payment was only provided for financial risky choices.

8 Respondents were paid for only one of their choices at the end of the experiment to prevent house-money and other “wealth” effects.

9 Dyer and Jia reconcile EU models and relative risk—return models by hypothesizing tradeoff coefficients (*b*) that will do so and, in particular, making *b* a function of EV(X).

Table 1. Listing of choice pairs included in meta-analysis of human choice data

Authors	Number of Choice Pairs	Avg. n	Gender	Age	Nationality	Decision Domain	Outcome Frame	Zero Outcome	Hypothetical Decision	Advance Payment
Kahneman & Tversky, 1984	1	152	b	y	american	human lives	gains	y	y	n
	1	155	b	y	american	human lives	losses	y	y	n
	1	150	b	y	american	money	losses	y	y	n
Highhouse & Paese, 1996	2	54	b	y	american	jobs	gains	y	y	n
	2	54	b	y	american	jobs	losses	y	y	n
	2	45	b	y	american	money	gains	y	y	n
	2	45	b	y	american	money	losses	y	y	n
Takemura, 1993	2	79	b	y	japanese	money	gains	y	y	n
	2	79	b	y	japanese	money	losses	y	y	n
Takemura, 1994	4	45	b	y	japanese	human lives	gains	y	y	n
	4	45	b	y	japanese	human lives	losses	y	y	n
Fagley & Miller, 1990	2	33	m	y	american	human lives	gains	y	y	n
	2	41	f	y	american	human lives	gains	y	y	n
	2	35	m	y	american	human lives	losses	y	y	n
	2	41	f	y	american	human lives	losses	y	y	n
	2	33	m	y	american	student lives	gains	y	y	n
	2	41	f	y	american	student lives	gains	y	y	n
	2	35	m	y	american	student lives	losses	y	y	n
	2	41	f	y	american	student lives	losses	y	y	n
Wang, 1996	4	31	b	y	american	human lives	gains	y	y	n
	4	31	b	y	american	human lives	losses	y	y	n
	1	33	b	y	american	lives of relative	gains	y	y	n
	1	31	b	y	american	lives of relative	losses	y	y	n
	4	42	b	y	american	paintings	gains	y	y	n
	4	40	b	y	american	paintings	losses	y	y	n
	4	34	b	y	american	money	gains	y	y	n
	4	31	b	y	american	money	losses	y	y	n
Fagley & Miller, 1987	1	44	b	x	american	human lives	gains	y	y	n
	1	42	b	x	american	human lives	losses	y	y	n
van Schie & van der Plight, 1987	2	117	b	y	british	human lives	losses	n	y	n
	2	88	b	y	british	time	losses	n	y	n
	4	48	b	y	dutch	human lives	losses	n	y	n
	2	48	b	y	dutch	jobs	losses	n	y	n
Wang & Johnston, 1995	5	46	b	y	american	human lives	gains	y	y	n
	5	46	b	y	american	human lives	losses	y	y	n
	1	50	b	y	american	lives of relative	gains	y	y	n
	1	50	b	y	american	lives of relative	losses	y	y	n
Leclerc, Schmitt, & Dube, 1995	3	97	b	y	american	time	losses	n	y	n
	1	47	b	y	american	time	gains	n	y	n

	1	36	b	y	american	money	losses	n	y	n
Schneider, 1992	9	25	b	y	american	human lives	gains	y	y	n
	9	20	b	y	american	human lives	losses	n	y	n
	6	25	b	y	american	animal lives	gains	y	y	n
	6	20	b	y	american	animal lives	losses	n	y	n
	3	25	b	y	american	student lives	gains	y	y	n
	3	25	b	y	american	student lives	losses	n	y	n
	6	20	b	y	american	jobs	gains	y	y	n
	6	25	b	y	american	jobs	losses	n	y	n
	3	20	b	y	american	money	gains	y	y	n
	3	25	b	y	american	money	losses	n	y	n
Highhouse & Yuce, 1996	1	118	b	y	american	human lives	gains	y	y	n
	1	112	b	y	american	human lives	losses	y	y	n
Thaler & Johnson, 1990	3	111	b	y	american	money	gains	n	n	n
	2	111	b	y	american	money	losses	n	n	n
	1	111	b	y	american	money	losses	y	n	n
	2	46	b	a	american	money	gains	n	y	n
	2	58	b	a	american	money	losses	n	y	n
Laughhunn & Payne, 1984	8	39	b	a	american	money	gains	n	y	y
	8	39	b	a	american	money	gains	n	y	n
Schoemaker, 1990	1	214	b	a	american	money	gains	y	y	n
	1	214	b	a	american	money	losses	y	y	n
Musser & Patrick, 1995	4	108	b	a	american	money	gains	y	y	y
	4	108	b	a	american	money	losses	y	y	y
Kahneman & Tversky, 1979	1	70	b	m	israeli	money	gains	y	y	y
	1	70	b	m	israeli	money	losses	y	y	y
	1	72	b	m	israeli	money	gains	y	y	n
	1	72	b	m	israeli	money	losses	y	y	n
Hsee & Weber, 1997	5	73	b	y	american	money	gains	y	y	n
	5	73	b	y	american	money	losses	y	y	n
	2	82	b	y	china	money	gains	y	y	n
	2	76	b	y	china	money	losses	y	y	n

Table 2: Results of regression analysis of proportion of respondents choosing the sure-thing option, separately for gain and for loss framed choices, but including all decision content domains.

a) Choices between Gains

Source	**DF**	**F Value**	**Pr > F**	**R-Square**
Model	20	6.79	<.0001	.62
Error	82			
Corrected Total	102			

		Type I SS		**Type III SS**	
Source	**DF**	**F-Value**	**p-value**	**F-Value**	**p-value**
Gender	2	2.97	.06	1.67	.19
Age	2	1.03	.36	1.40	.25
National	2	0.42	.65	2.63	.08
Absolute Outcome Sign	1	20.29	.0001	6.45	.02
Advance Payment	1	2.49	.12	1.94	.17
Outcomes for Real	1	12.79	.001	8.07	.005
Domain	7	2.64	.02	1.90	.08
P(low outcome)	1	59.42	<.0001	30.62	<.0001
Zero Outcome	1	1.60	.21	0.06	.81
CV	1	7.56	.007	4.28	.05
P(low)*CV	1	4.27	.05	4.27	.05

b) Choices between Losses

Source	**DF**	**F Value**	**Pr > F**	**R-Square**
Model	22	4.00	<.0001	.53
Error	78			
Corrected Total	100			

		Type I SS		**Type III SS**	
Source	**DF**	**F-Value**	**p-value**	**F-Value**	**p-value**
Gender	2	0.95	.39	0.64	.52
Age	2	4.68	.02	1.94	.15
National	4	1.67	.17	3.49	.02
Absolute Outcome Sign	1	1.53	.22	1.36	.25
Advance Payment	1	3.69	.06	7.86	.007
Outcomes for Real	1	7.75	.007	10.21	.002
Domain	7	6.46	<.0001	7.41	<.0001
P(low outcome)	1	2.56	.12	3.04	.09
Zero Outcome	1	0.01	.94	0.47	.49
CV	1	2.08	.15	8.16	.006

P(low)*CV	1	7.19	.01	7.19	.01

Table 3: Results of regression analysis of proportion of respondents choosing the sure-thing option in choices involving monetary outcomes, separately for gain and loss framed choices.

a) Choices between Financial Gains

Source	**DF**	**F Value**	**Pr > F**	**R-Square**
Model	10	5.67	<.0001	.62
Error	35			
Corrected Total	45			

		Type I SS		**Type III SS**		
Source	**DF**	**F-Value**	**p-value**	**F-Value**	**p-value**	
Age	1	1.29	.26	3.72	.06	
National	2	1.63	.21	3.45	.05	
Absolute Outcome Sign	1	12.09	.002	6.24	.02	
Advance Payment	1	0.43	.51	0.74	.39	
Outcomes for Real	1	22.40	<.0001	4.94	.04	
P(low outcome)	1	4.23	.05	6.93	.02	
Zero Outcome	1	1.70	.20	6.05	.02	
EV	1	8.96	.006	8.66	.006	
CV	1	2.60	.11	2.60	.11	
EV	1	8.09	.01	0.00	.96	
Var	1	0.00	.96	0.00	.96	R^2 = .58
EV	1	6.79	.02	1.44	.24	
SD	1	1.45	.23	1.45	.24	R^2 = .59

b) Choices between Financial Losses

Source	**DF**	**F Value**	**Pr > F**	**R-Square**
Model	10	3.42	.009	.62
Error	21			
Corrected Total	31			

		Type I SS		**Type III SS**		
Source	**DF**	**F-Value**	**p-value**	**F-Value**	**p-value**	
Age	1	9.77	.005	2.18	.15	
National	2	2.18	.15	0.08	.92	
Absolute Outcome Sign	1	0.09	.77	0.26	.62	
Advance Payment	1	2.75	.11	4.37	.05	
Outcomes for Real	1	10.50	.004	8.28	.009	
P(low outcome)	1	1.65	.22	0.37	.55	
Zero Outcome	1	1.08	.31	4.82	.04	
EV	1	1.24	.28	0.52	.47	
CV	1	2.75	.11	2.75	.11	
EV	1	1.16	.29	2.08	.17	
Var	1	1.13	.30	1.13	.30	$R^2 = .59$
EV	1	1.36	.26	0.36	.55	
SD	1	0.09	.77	0.09	.77	$R^2 = .56$

Table 4

Choice pair characteristics, observed response proportions for sure-thing option, weighted return and decision field theory model predictions for cardgame experiment.

Sure Thing	Gamble	Variance	CV	P(ST)	Weighted Return Model	Decision Field Theory
$1	($0, .9; $10, .9)	9	300	.68	.73	.56
$3	($0, .5; $6, .5)	9	100	.39	.57	.40
$9	($0, .1; $10, .9)	9	33	.24	.49	.24
$1	($0, .5; $2, .5)	1	100	.58	.58	.50
$3	($0, .5; $6, .5)	9	100	.39	.57	.40
$6	($0, .5; $12, .5)	36	100	.42	.57	.40

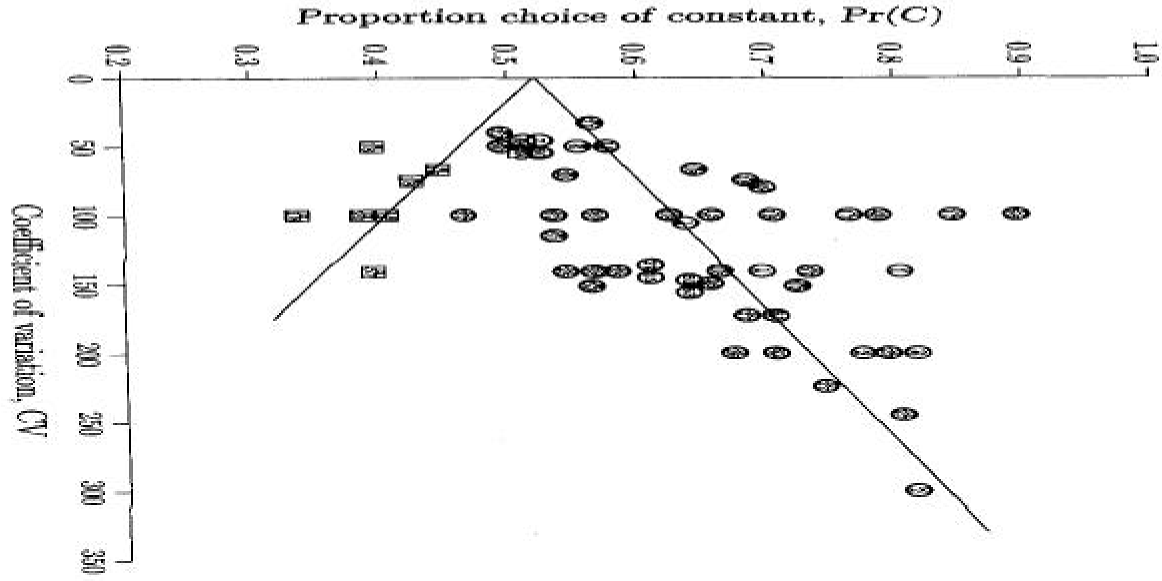
Proportion choice of constant, Pr(C)
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0
50
100
150
200
250
300
350
Coefficient of variation, CV

Figure 1

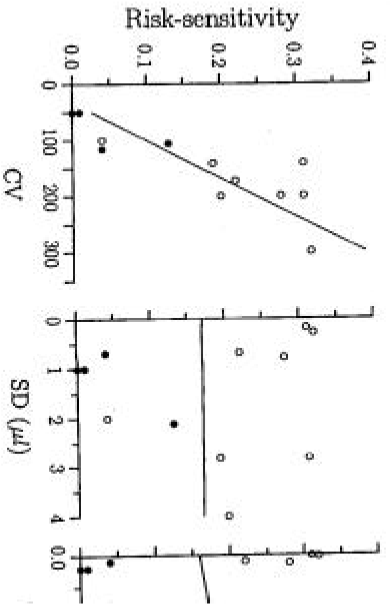

Figure 2

Figure 3