Uncertainty Equivalents: Testing the Limits of the Independence Axiom*

James Andreoni†
University of California, San Diego
and NBER

Charles Sprenger‡
Stanford University

April, 2010
This Version: August 28, 2012

Abstract

There is convincing experimental evidence that Expected Utility fails, but when does it fail, how severely, and for what fraction of subjects? We explore these questions using a novel measure we call the uncertainty equivalent. We find Expected Utility performs well away from certainty, but fails primarily near certainty. Among non-Expected Utility theories, the violations are in contrast to familiar formulations of Cumulative Prospect Theory. A further surprise is that nearly 40% of subjects indirectly violate first order stochastic dominance, preferring certainty of a low outcome to a near-certain, dominant gamble. Interestingly, these dominance violations have predictive power in standard experimental techniques eliciting prospect theory relations.

JEL classification: D81, D90

Keywords: Uncertainty.

*We are grateful for the insightful comments of many colleagues, including Nageeb Ali, Colin Camerer, Vince Crawford, David Dillenberger, Yoram Halevy, Uri Gneezy, Faruk Gul, Ori Heffetz, David Laibson, Mark Machina, William Neilson, Jawwad Noor, Ted O'Donoghue, Pietro Ortoleva, Wolfgang Pesendorfer, Matthew Rabin, Uri Simonsohn, Joel Sobel, and Peter Wakker. Special thanks are owed to Lise Vesterlund and the graduate experimental economics class at the University of Pittsburgh. We also acknowledge the generous support of the National Science Foundation Grant SES1024683 to Andreoni and Sprenger, and SES0962484 to Andreoni.

†University of California at San Diego, Department of Economics, 9500 Gilman Drive, La Jolla, CA 92093; andreoni@ucsd.edu.

‡Stanford University, Department of Economics, Landau Economics Building, 579 Serra Mall, Stanford, CA 94305; cspreng@stanford.edu

1 Introduction

The theory of Expected Utility (EU) is among the most elegant and esthetically pleasing results in all of economics. It shows that if a preference ordering over a given set of gambles is complete, transitive, continuous, and, in addition, it satisfies the independence axiom, then utility is linear in objective probabilities.[1] The idea that a gamble's utility *could* be represented by the mathematical expectation of its utility outcomes dates to the St. Petersburg Paradox (Bernouilli, 1738). The idea that a gamble's utility was necessarily such an expectation if independence and the other axioms were satisfied became clear only in the 1950's (Samuelson, 1952, 1953).[2]

Two parallel research tracks have developed with respect to the independence axiom. The first takes linearity-in-probabilities as given and fits functional forms of the utility of consumption to experimental data (Holt and Laury, 2002).[3] The second track focuses on identifying violations of independence.[4] Principal among these are Allais' (1953b) well documented and extensively replicated common consequence and common ratio paradoxes.[5]

These and other violations of EU motivated new theoretical and experimental ex-

[1]Subjective Expected Utility is not discussed in this paper. All results will pertain only to objective probabilities.

[2]The independence axiom is closely related to the Savage (1954) 'sure-thing principle' for subjective expected utility (Samuelson, 1952). Expected utility became known as von Neumann-Morgenstern (vNM) preferences after the publication of von Neumann and Morgenstern (1944). Independence, however, was not among the discussed axioms, but rather implicitly assumed. Samuelson (1952, 1953) discusses the resulting confusion and his suspicion of an implicit assumption of independence in the vNM treatment. Samuelson's suspicion was then confirmed in a note by Malinvaud (1952). For an excellent discussion of the history of the independence axiom, see Fishburn and Wakker (1995).

[3]Harrison and Rutstrom (2008) provide a detailed summary of both the experimental methods and estimation exercises associated with this literature.

[4]This second line of research began contemporaneously with the recognition of the importance of the independence axiom. Indeed Allais' presentation of Allais (1953a) was in the same session as Samuelson's presentation of Samuelson (1953) and the day after Savage's presentation of Savage (1953) at the Colloque Internationale d'Econométrie in Paris in May of 1952.

[5]In addition to the laboratory replications of Kahneman and Tversky (1979); Tversky and Kahneman (1992), there is now an extensive catalogue of Allais style violations of EU (Camerer, 1992; Harless and Camerer, 1994; Starmer, 2000). Other tests have demonstrated important failures of EU beyond the Allais Paradox (Allais, 1953b). These include the calibration theorem (Rabin, 2000a,b), and goodness-of-fit comparisons (Camerer, 1992; Hey and Orme, 1994; Harless and Camerer, 1994).

ercises, the most noteworthy being Cumulative Prospect Theory's (CPT) inverted S-shaped non-linear probability weighting (Kahneman and Tversky, 1979; Quiggin, 1982; Tversky and Kahneman, 1992; Tversky and Fox, 1995). In a series of experiments eliciting certainty equivalents for gambles, Tversky and Kahneman (1992) and Tversky and Fox (1995) estimated utility parameters supporting a model in which subjects "edit" probabilities by down-weighting high probabilities and up-weighting low probabilities. Identifying the S-shape of the weighting function and determining its parameter values has received significant attention both theoretically and in experiments (Wu and Gonzalez, 1996; Prelec, 1998; Gonzalez and Wu, 1999; Abdellaoui, 2000).[6]

Perhaps suprisingly, there are few direct tests of the independence axiom's most critical implication: linearity-in-probabilities of the expected utility function. If, as in the first branch of literature, the independence axiom is assumed for identification of utility parameters, then the axiom cannot be rejected. Likewise, in the second branch, tests of probability weighting often are not separate from functional form assumptions and thus are unlikely to confirm the independence axiom if it in fact holds unless, of course, both consumption utility and the weighting function are correctly specified.[7]

In this paper, we provide a simple direct test of linearity-in-probabilities that reveals when independence holds, how it fails, and the nature of violations. We reintroduce an experimental method, which we call the *uncertainty equivalent*. Whereas a certainty equivalent identifies the certain amount that generates indifference to a given gamble, the uncertainty equivalent identifies the probability mixture over the gamble's best outcome and zero that generates indifference. For example, consider a $(p, 1-p)$ gamble over \$10 and \$30, $(p; 10, 30)$. The uncertainty equivalent identifies the $(q, 1-q)$ gamble

[6]Based upon the strength of these findings researchers have developed new methodology for eliciting risk preferences such as the 'trade-off' method (Wakker and Deneffe, 1996) that is robust to non-linear probability weighting.

[7]This observation is made by Abdellaoui (2000). Notable exceptions are the non-parametric probability weighting estimates of Gonzalez and Wu (1999); Bleichrodt and Pinto (2000) and Abdellaoui (2000) which find support for non-linearity-in-probabilities (see sub-section 4.2 for discussion).

over \$30 and \$0, $(q; 30, 0)$, that generates indifference.[8] Independence implies a linear relationship between p and q. The uncertainty equivalent draws its motivation from the derivation of expected utility, where the cardinal index for a gamble is derived as the probability mixture over the best and worst options in the space of gambles.[9] This means that in an uncertainty equivalent measure, the elicited q in $(q; Y, 0)$ can be interpreted as a utility index for the p gamble, $(p; X, Y)$, when $Y > X > 0$.

The uncertainty equivalent can be used to inform the discussion of a variety of non-EU preference models including S-shaped probability weighting.[10] Importantly, in the uncertainty equivalent environment, these predictions are independent of the functional form of utility. Hence, unlike the exercises described above, uncertainty equivalents can explore the nature of probability distortions without potential confounds of functional forms.

We conducted a within-subject experiment with 76 undergraduates at the University of California, San Diego, using both uncertainty and certainty equivalents. Using

[8]We recognize that it is a slight abuse of traditional notation to have the probability refer to the lower outcome in the given gamble and the higher outcome in the uncertainty equivalent. It does, however, ease explication to have p refer to the probability of the low value and q refer to the probability of the high value.

[9]Such derivations are provided in most textbook treatments of expected utility. See, e.g. Varian (1992). We should be clear to distinguish the uncertainty equivalent from a 'probability equivalent'. A probability equivalent elicits the probability of winning that makes a gamble indifferent to a *sure* amount. Uncertainty equivalents have risk on both sides of the indifference condition. Our research has uncovered that methods like our uncertainty equivalent were discussed in Farquhar's (1984) excellent survey of utility assessment methods and, to our knowledge, were implemented experimentally in only one study of nine subjects using hypothetical monetary rewards (McCord and de Neufville, 1986), and a number of medical questionnaires (Magat, Viscusi and Huber, 1996; Oliver, 2005, 2007; Bleichrodt, Abellan-Perinan, Pinto-Prades and Mendez-Martinez, 2007). One important difference between these techniques and our own is that prior research elicited the gamble $(q; Y, 0)$ indifferent to an assessment gamble $(p; X, 0)$ and not $(p; X, Y)$. This distinction is important since if the gambles share a common low outcome, the researcher cannot easily separate competing behavioral decision theories around $p = 1$, as we show.

[10]Additional models that deliver specific predictions in the uncertainty equivalent environment are expectations-based reference-dependence such as disappointment aversion (Bell, 1985; Loomes and Sugden, 1986; Gul, 1991) and "u-v" preferences (Neilson, 1992; Schmidt, 1998; Diecidue, Schmidt and Wakker, 2004). These models capture the intuition of Allais (1953b) that when options are far from certain, individuals act effectively as EU maximizers but, when certainty is available, it is disproportionately preferred. The u-v model differs in important ways from extreme or even discontinuous probability weighting and prior experiments have demonstrated these differences (Andreoni and Sprenger, 2011).

uncertainty equivalents we find that p and q are, quite strikingly, related linearly for values of p away from certainty. This linearity breaks down as probabilities approach 1, violating expected utility. Interestingly, the nature of the violation stands in stark contrast to standard S-shaped formulations of cumulative prospect theory. However, when we turn to our certainty equivalents data, these same subjects reproduce with precision the standard finding of S-shaped weighting. These apparently disparate findings are linked by a puzzling fact. Nearly 40% of our subjects in the uncertainty equivalent environment demonstrate a surprising preference for certainty. These subjects exhibit a higher uncertainty equivalent for a certain, low outcome than for a nearby dominant gamble offering this low outcome with probability 0.95 and something greater otherwise. This indirect violation of first order stochastic dominance, akin to the recently debated 'uncertainty effect'(Gneezy, List and Wu, 2006; Rydval, Ortmann, Prokosheva and Hertwig, 2009; Keren and Willemsen, 2008; Simonsohn, 2009), has substantial predictive power. Subjects who violate stochastic dominance are significantly more likely to exhibit hallmarks of S-shaped probability weighting in their certainty equivalents behavior.

Understanding these results, particularly the predictive power of dominance violations in delivering standard prospect theory shapes, presents a key challenge. Violations of first order stochastic dominance is a normatively unappealing feature of a theory of decision-making under uncertainty, while the prospect theoretic S-shapes are often thought to be a primitive, grounded in individuals' reactions to changing probabilities. Our results are problematic for the potentially attractive view of seeing stochastic dominance violations as mistakes and probability weighting as a preference. The two phenomena correlate at a high level. Clearly, more work is necessary to understand the source of these phenomena. In one suggestive, but far from conclusive exercise we indicate that specific preferences for certainty as in "u-v" preferences (Neilson, 1992; Schmidt, 1998; Diecidue et al., 2004) or disappointment aversion (Bell, 1985; Loomes and Sugden, 1986; Gul, 1991) can generate the dominance violations of the uncertainty equivalents, especially if there are small decision or measurement errors, and account at least partially for the probability weighting of the certainty equivalents.[11] This exercise indicates that probability weighting, as often elicited in certainty-based experiments may be an artifact of specific preferences for certainty coupled with specification error.

Our experiments are, of course, not the first to recognize the importance of certainty. The original Allais (1953b) paradoxes drew attention to certainty being "disproportionately preferred," and others have noted the preponderance of the evidence against EU implicates certainty as a factor (Conlisk, 1989; Camerer, 1992; Harless and Camerer, 1994; Starmer, 2000). Recognizing that certainty may be preferred gives a reason, perhaps, to expect non-EU behavior in experimental methodologies such as certainty equivalents: Allais style certainty effects are built into the experimental design.

The paper continues as follows. Section 2 discusses the uncertainty equivalent methodology and develops predictions based on different preference models. Section 3 presents experimental design details. Section 4 presents results and Section 5 presents a corresponding discussion. Section 6 concludes.

2 The Uncertainty Equivalent

Consider a lottery $(p; X, Y)$ which provides $\$X$ with probability p and $\$Y > \$X$ with probability $1 - p$. A certainty equivalent task elicits the certain amount, $\$C$, that is indifferent to this gamble. The uncertainty equivalent elicits the q-gamble over \$Y and \$0, $(q; Y, 0)$, that is indifferent to this gamble. Take for example a 50%-50% gamble paying either \$10 or \$30. The uncertainty equivalent is the q-gamble over \$30 and \$0

[11] Importantly, some disappointment averse models are constructed with assumptions guaranteeing that the underlying preferences satisfy stochastic dominance, taking violations of stochastic dominance as a disqualifying feature of a model of behavior (Loomes and Sugden, 1986; Gul, 1991), while others are not (Bell, 1985). We remain agnostic about whether violations of dominance reflect true preferences, or are a result of a preference for certainty, as in disappointment aversion or u-v preferences, coupled with noise. Exploring such a distinction is an interesting question for future research.

that generates indifference.

Under standard preference models, a more risk averse individual will, for a given gamble, have a lower certainty equivalent, C, and a higher uncertainty equivalent, q. A powerful distinction of the uncertainty equivalent is, however, that it is well-suited to identifying alternative preference models such as S-shaped probability weighting, where the non-linearity of the weighting function can be recovered directly. Though the uncertainty equivalent method could be easily applied to the estimation of parameters for specific models of decision-making, these exercises are left to future work. Given the potential sensitivity of parameter values to variations in the decision environment, we instead focus on qualitative differences based on implied shape predictions.

2.1 Predictions

We present empirical predictions in the uncertainty equivalent environment for expected utility and S-shaped probability weighting.[12] Unlike experimental contexts that require functional form assumptions for model identification, the uncertainty equivalent can provide tests of these specifications based on the relationship between p and q without appeal to specific functional form for utility.

2.1.1 Expected Utility

Consider a gamble with probability p of $\$X$ and probability $1-p$ of a larger payment $\$Y > \$X$. The uncertainty equivalent of this prospect is the value q satisfying

$$p \cdot u(X) + (1-p) \cdot u(Y) = q \cdot u(Y) + (1-q) \cdot u(0).$$

[12] We also provide some predictions based on disappointment aversion, and u-v preferences in Section 5. This is, of course, a limited list of the set of potentially testable decision models. For example, we do not discuss the anticipatory utility specifications of Kreps and Porteus (1978) and Epstein and Zin (1989) as experimental uncertainty was resolved during the experimental sessions. These models generally reduce to expected utility when uncertainty is resolved immediately.

Assuming u(0) $= 0$, $u(Y) > u(X)$, and letting $\theta = u(X)/u(Y) < 1$, then

$$q = p \cdot \frac{u(X)}{u(Y)} + 1 - p = 1 - p \cdot (1 - \theta),$$

and

$$\frac{dq}{dp} = \frac{u(X)}{u(Y)} - 1 = -(1 - \theta) < 0.$$

Thus, expected utility generates a negative *linear* relationship between the probability p of $\$X$ and the probability q of $\$Y$. This is an easily testable prediction.

2.1.2 Cumulative Prospect Theory Probability Weighting

Under Cumulative Prospect Theory, probabilities are weighted by the non-linear function $\pi(p)$.[13] One popular functional form to which we give specific attention is the one parameter function used in Tversky and Kahneman (1992)[14], $\pi(p) = p^\gamma/(p^\gamma + (1-p)^\gamma)^{1/\gamma}$, $0 < \gamma < 1$. This inverted S-shaped function, as with others used in the literature, has the property that $\pi'(p)$ approaches infinity as p approaches 0 or 1. Probability weights are imposed on the higher of the two utility values.[15]

Under this CPT formulation, the uncertainty equivalent indifference condition is

$$(1 - \pi(1-p)) \cdot u(X) + \pi(1-p) \cdot u(Y) = \pi(q) \cdot u(Y) + (1 - \pi(q)) \cdot u(0).$$

[13]The key difference between Cumulative Prospect Theory and the original formulation posed in Kahneman and Tversky (1979) is weighting of the cumulative distribution as opposed to weighting each probability separately. In Appendix A.1, we provide additional analysis for non-cumulative prospect theory which generates broadly similar predictions in the implemented uncertainty equivalent environments to Cumulative Prospect Theory.

[14]Tversky and Fox (1995) and Gonzalez and Wu (1999) employ a similar two parameter $\pi(p)$ function. See Prelec (1998) for alternative S-shaped specifications.

[15]This formulation is assumed for binary gambles over strictly positive outcomes in Kahneman and Tversky (1979) and for all gambles in Tversky and Kahneman (1992). We abstract away from prospect theory's fixed reference point formulation as static reference points do not alter the analysis.

Again letting $u(0) = 0$ and $\theta = u(X)/u(Y) < 1$,

$$(1 - \pi(1-p)) \cdot \theta + \pi(1-p) = \pi(q).$$

This implicitly defines q as a function of p, yielding

$$\frac{dq}{dp} = -\frac{\pi'(1-p)}{\pi'(q)} \cdot [1-\theta] < 0.$$

As with expected utility, q and p are negatively related. Contrary to expected utility, the rate of change, dq/dp, depends on both p and q. Importantly, as p approaches 1, $\pi'(1-p)$ approaches infinity and, provided finite $\pi'(q)$, the slope dq/dp becomes increasingly negative.[16] This is a clearly testable alternative to expected utility.

Importantly, the argument does not rest on the derivatives of the probability weighting function. Any modified S-shaped weighting function featuring up-weighting of low probabilities and down-weighting of high probabilities will share the characteristic that the relationship between q and p will become more negative as p approaches 1. This would be the case for virtually all functional forms and parameter values discussed in Prelec (1998) and for functions respecting condition (A) of the Quiggin (1982) weighting function. Take p close to 1 and $(1-p)$ close to zero, $u(Y)$ will be up-weighted and $u(X)$ will be down-weighted on the left hand side of the above indifference condition.

[16]It is difficult to create a general statement for all probabilities between zero and one based upon the second derivative d^2q/dp^2, as the second derivatives of the weighting function can be positive or negative depending on the concavity or convexity of the S-shaped distortion. The second derivative is

$$\frac{d^2q}{dp^2} = \frac{\pi''(1-p) \cdot [1-\theta] \cdot \pi'(q) + \pi''(q)\frac{dq}{dp} \cdot \pi'(1-p) \cdot [1-\theta]}{\pi'(q)^2}.$$

However, for p near 1, the sign is partially determined by $\pi''(q)$ which may be negative or positive. For S-shaped weighting, $\pi''(1-p)$ will be negative in the concave region of low probabilities, and dq/dp will be negative from the development above. If q lies in the convex weighting region, such that $\pi''(q) > 0$, then $d^2q/dp^2 < 0$ and the relationship is concave and may remain so with $\pi''(q) < 0$. Consensus puts the concave region between probability 0 and around 1/3 (Tversky and Kahneman, 1992; Tversky and Fox, 1995; Prelec, 1998). As will be seen, the uncertainty equivalents for $p = 1$ lie substantially above 1/3 for all of our experimental conditions such that a concave relationship between p and q would be expected.

In order to compensate for the up-weighting of the good outcome on the left hand side, q on the right hand side must be high. At $p = 1$, the up-weighting of $u(Y)$ disappears precipitously and so q decreases precipitously to maintain indifference.

To assess the power of the conducted tests in the domain of S-shaped probability weighting we simulate data in our experimental environment for the probability weighting formulation and parameter finding of Tversky and Kahneman (1992) ($\gamma = 0.61$). This simulation exercise is detailed in Appendix A.1, demonstrating that a substantial concave relationship is obtained both through regression analysis and non-parametric test statistics at parameter levels generally estimated in the experimental literature.

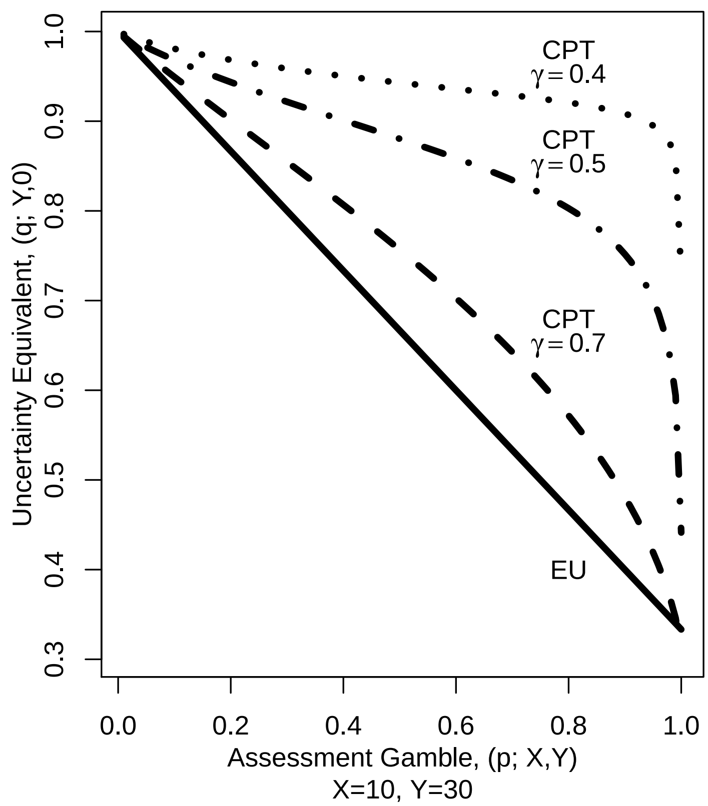
Figure 1 presents the theoretical predictions of the EU and S-shaped probability weighting of the form proposed by Tversky and Kahneman (1992), $\pi(p) = p^\gamma/(p^\gamma+(1-p)^\gamma)^{1/\gamma}$, with $\gamma \in \{0.4, 0.5, 0.7\}$. Importantly, the uncertainty equivalent environment provides clear separation between the CPT S-shaped probability weighting and EU regardless of the form of utility. Under expected utility, q should be a linear function of p. Under S-shaped probability weighting, q should be a concave function of p with the relationship growing more negative as p approaches 1.

3 Experimental Design

Eight uncertainty equivalents were implemented with probabilities $p \in \{0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, 1\}$ in three different payment sets, $(X, Y) \in \{(10, 30), (30, 50), (10, 50)\}$, yielding 24 total uncertainty equivalents. The experiment was conducted with paper-and-pencil and each payment set (X, Y) was presented as a packet of 8 pages. The uncertainty equivalents were presented in increasing order from $p = 0.05$ to $p = 1$ in a single packet.

On each page, subjects were informed that they would be making a series of decisions between two options. Option A was a p chance of receiving \$$X$ and a $1-p$ chance of receiving \$$Y$. Option A remained the same throughout the page. Option B varied in

Figure 1: Empirical Predictions



Note: Empirical predictions of the relationship between assessment gambles, $(p; X, Y)$, and uncertainty equivalents $(q; Y, 0)$ for Expected Utility, and S-shaped CPT probability weighting with $\pi(p) = p^\gamma/(p^\gamma + (1-p)^\gamma)^{1/\gamma}$, $\gamma \in \{0.4, 0.5, 0.7\}$. Apart from probability distortions linear utility is assumed with $X = 10, Y = 30$ used for the figure.

steps from a 5 percent chance of receiving $\$Y$ and a 95 percent chance of receiving \$0 to a 99 percent chance of receiving $\$Y$ and a 1 percent chance of receiving \$0. Figure 2, Panel A provides a sample decision task. In this price list style experiment, the row at which a subject switches from preferring Option A to Option B indicates the range of values within which the uncertainty equivalent, q, lies.

A common frustration with price lists is that anywhere from 10 to 50 percent of

Figure 2: Sample Uncertainty Equivalent and Certainty Equivalent Tasks

Panel A : Uncertainty Equivalent

	Option A			or	Option B		
	Chance of \$10	Chance of \$30			Chance of \$0	Chance of \$30	
	50 in 100	50 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	50 in 100	50 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	50 in 100	50 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	50 in 100	50 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	50 in 100	50 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	50 in 100	50 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	50 in 100	50 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	50 in 100	50 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	50 in 100	50 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	50 in 100	50 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	50 in 100	50 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	50 in 100	50 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	50 in 100	50 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	50 in 100	50 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	50 in 100	50 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	50 in 100	50 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	50 in 100	50 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	50 in 100	50 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	50 in 100	50 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	50 in 100	50 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	50 in 100	50 in 100	☐	*or*	1 in 100	99 in 100	☐
	50 in 100	50 in 100	☐	*or*	0 in 100	100 in 100	☑

Panel B : Certainty Equivalent

	Option A			or	Option B	
	Chance of \$30	Chance of \$0			Sure Amount	
	50 in 100	50 in 100	☑	*or*	\$0.00 for sure	☐
1)	50 in 100	50 in 100	☐	*or*	\$0.50 for sure	☐
2)	50 in 100	50 in 100	☐	*or*	\$1.00 for sure	☐
3)	50 in 100	50 in 100	☐	*or*	\$1.50 for sure	☐
4)	50 in 100	50 in 100	☐	*or*	\$2.50 for sure	☐
5)	50 in 100	50 in 100	☐	*or*	\$3.50 for sure	☐
6)	50 in 100	50 in 100	☐	*or*	\$4.50 for sure	☐
7)	50 in 100	50 in 100	☐	*or*	\$6.50 for sure	☐
8)	50 in 100	50 in 100	☐	*or*	\$8.50 for sure	☐
9)	50 in 100	50 in 100	☐	*or*	\$10.50 for sure	☐
10)	50 in 100	50 in 100	☐	*or*	\$13.50 for sure	☐
11)	50 in 100	50 in 100	☐	*or*	\$16.50 for sure	☐
12)	50 in 100	50 in 100	☐	*or*	\$19.50 for sure	☐
13)	50 in 100	50 in 100	☐	*or*	\$21.50 for sure	☐
14)	50 in 100	50 in 100	☐	*or*	\$23.50 for sure	☐
15)	50 in 100	50 in 100	☐	*or*	\$25.50 for sure	☐
16)	50 in 100	50 in 100	☐	*or*	\$26.50 for sure	☐
17)	50 in 100	50 in 100	☐	*or*	\$27.50 for sure	☐
18)	50 in 100	50 in 100	☐	*or*	\$28.50 for sure	☐
19)	50 in 100	50 in 100	☐	*or*	\$29.00 for sure	☐
20)	50 in 100	50 in 100	☐	*or*	\$29.50 for sure	☐
	50 in 100	50 in 100	☐	*or*	\$30.00 for sure	☑

subjects can be expected to switch columns multiple times.[17] Because such multiple switch points are difficult to rationalize and may indicate subject confusion, it is common for researchers to drop these subjects from the sample.[18] Instead, we augmented the standard price list with a simple framing device designed to clarify the decision process. In particular, we added a line to both the top and bottom of each price list in which the choices were clear, and illustrated this by checking the obvious best option. The top line shows that each p-gamble is preferred to a 100 percent chance of receiving \$0 while the bottom line shows that a 100 percent chance of receiving \$$Y$ is preferred to each p-gamble. These pre-checked gambles were not available for payment, but were used to clarify the decision task. This methodology is close to the clarifying instructions from the original Holt and Laury (2002), where subjects were described a 10 lottery choice task and random die roll payment mechanism and then told, "In fact, for Decision 10 in the bottom row, the die will not be needed since each option pays the highest payoff for sure, so your choice here is between 200 pennies or 385 pennies."

Since the economist is primarily interested in the price list method as a means of measuring a single choice – the switching point – it seemed natural to include language to this end. Hence, in directions subjects were told "Most people begin by preferring Option A and then switch to Option B, so one way to view this task is to determine the best row to switch from Option A to Option B." Our efforts appear to have reduced the volume of multiple switching dramatically, to less than 1 percent of total responses. Individuals with multiple switch points are removed from analysis and are noted.

In order to provide an incentive for truthful revelation of uncertainty equivalents, subjects were randomly paid one of their choices in cash at the end of the experimental session.[19] This random-lottery mechanism, which is widely used in experimental

[17]Holt and Laury (2002) observed around 10 percent and Jacobson and Petrie (2009) observed nearly 50 percent multiple switchers. An approximation of a typical fraction of subjects lost to multiple switch points in an MPL is around 15 percent.

[18]Other options include selecting one switch point to be the "true point" (Meier and Sprenger, 2010) or constraining subjects to a single switch point (Harrison, Lau, Rutstrom and Williams, 2005).

[19]Please see the instructions in the Appendix for payment information provided to subjects.

economics, does introduce a compound lottery to the decision environment. In a series of experiments involving decisions over risky prospects, including those involving certainty, Starmer and Sugden (1991); Cubitt, Starmer and Sugden (1998) demonstrate that this mechanism generally does not suffer from contamination effects in practice. Seventy-six subjects were recruited from the undergraduate population at University of California, San Diego. The experiment lasted about one hour and average earnings were \$24.50, including a \$5 minimum payment.

3.1 Certainty Equivalents and Additional Risk Measures

In addition to the uncertainty equivalents discussed above, subjects faced 7 standard certainty equivalents tasks with p gambles over \$30 and \$0 from the set $p \in \{0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95\}$. These probabilities are identical to those used in the original probability weighting experiments of Tversky and Kahneman (1992) and Tversky and Fox (1995). The certainty equivalents were also presented in price list style with similar language to the uncertainty equivalents and could also be chosen for payment.[20] An example of our implemented certainty equivalents is presented in Figure 2, Panel B.

As a buffer between the certainty and uncertainty equivalents tasks, we also implemented two Holt and Laury (2002) risk measures over payment values of \$10 and \$30. Examples of these additional risk measures are provided in the appendix. Two orders of the tasks were implemented: 1) UE, HL, CE and 2) CE, HL, UE to examine order effects, and none were found. Though we used the HL task primarily as a buffer between certainty and uncertainty equivalents, a high degree of correlation is obtained across elicitation techniques. As the paper is already long, correlations with HL data

[20] Multiple switching was again greatly reduced relative to prior studies to less than 1 percent of responses. Individuals with multiple switch points are removed from analysis and are noted. As will be seen, results of the CE task reproduce the results of others. This increases our confidence that our innovations with respect to the price lists did not result in biased or peculiar measurement of behavior.

are discussed primarily in footnotes.

4 Results

We present our analysis in three sub-sections. First, we look at the uncertainty equivalents and provide tests of linearity at the aggregate level, documenting violations of expected utility close to probability 1. The nature of the violation is inconsistent with standard formulations of CPT S-shaped weighting. Second, we consider the standard certainty equivalents, reproducing the usual S-shaped probability weighting phenomenon. We link these two results in a third individual analysis sub-section investigating violations of first order stochastic dominance. We find that 38% of subjects exhibit dominance violations at probability 1 in our uncertainty equivalents and that the probability weighting identified in the certainty equivalents is driven by these individuals. Understanding this correlation is the subject of the subsequent discussion.

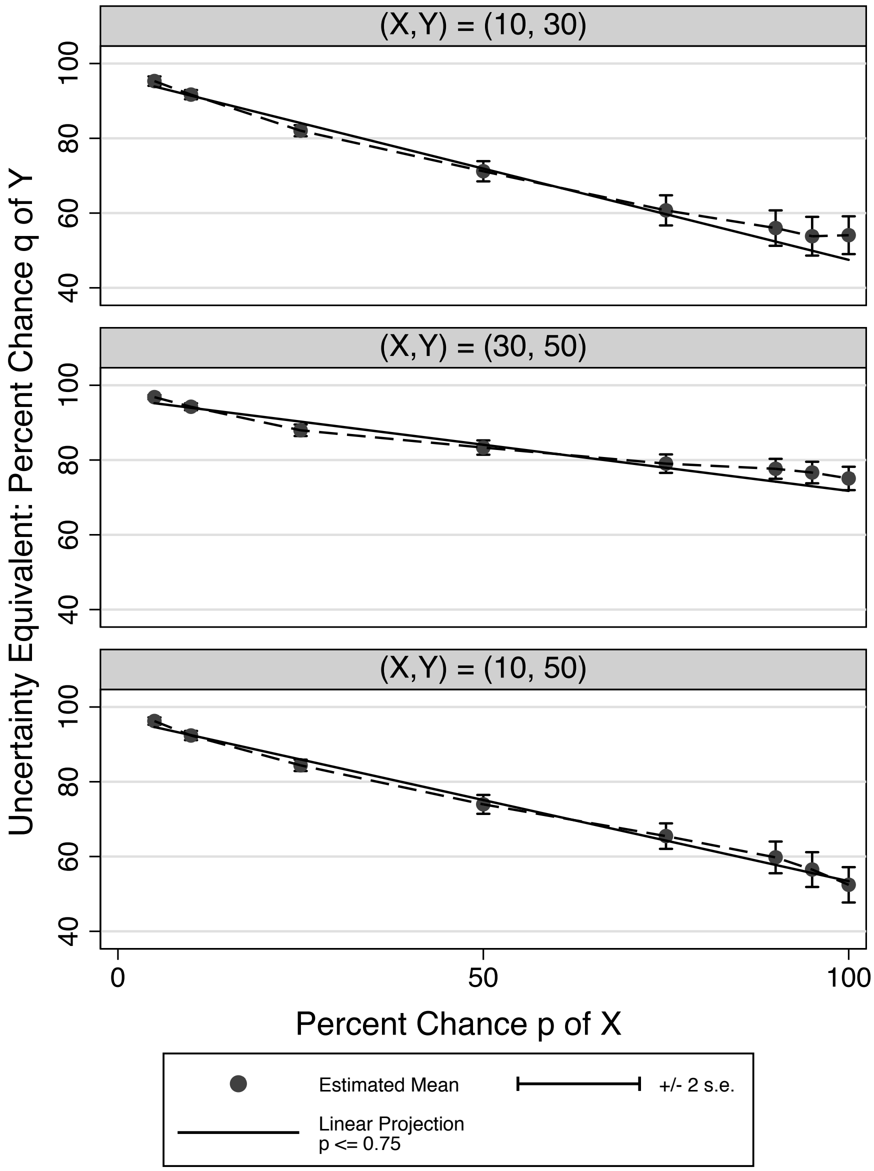
4.1 Uncertainty Equivalents and Tests of Linearity

To provide estimates of the mean uncertainty equivalent and the appropriate standard error for each of the 24 uncertainty equivalent tasks, we first estimate interval regressions (Stewart, 1983).[21] The interval response of q is regressed on indicators for all probability and payment-set interactions with standard errors clustered on the subject level. We calculate the relevant coefficients as linear combinations of interaction terms and present these in Table 1, Panel A. Figure 3 graphs the corresponding mean uncertainty equivalent, q, for each p, shown as dots with error bars.[22]

[21] Virtually identical results are obtained when using OLS and the midpoint of the interval.

[22] Uncertainty equivalents correlate significantly with the number of safe choices chosen in the Holt-Laury risk tasks. For example, for $p = 0.5$ the individual correlations between the uncertainty equivalent q and the number of safe choices, S_{10}, in the \$10 HL task are $\rho_{q(10,30),S_{10}} = 0.52$ ($p < 0.01$), $\rho_{q(30,50),S_{10}} = 0.38$ ($p < 0.01$), and $\rho_{q(10,50),S_{10}} = 0.54$ ($p < 0.01$). The individual correlations between the uncertainty equivalent, q, and the number of safe choices, S_{30}, in the \$30 HL task are $\rho_{q(10,30),S_{30}} = 0.54$ ($p < 0.01$), $\rho_{q(30,50),S_{30}} = 0.45$ ($p < 0.01$), and $\rho_{q(10,50),S_{30}} = 0.67$ ($p < 0.01$). The correlation between the number of safe choices in the HL tasks is also high, $\rho_{S_{10},S_{30}} = 0.72$ ($p < 0.01$).

Figure 3: Uncertainty Equivalent Responses



Note: Figure presents uncertainty equivalent, $(q; Y, 0)$, corresponding to Table 1, Panel A for each given gamble, $(p; X, Y)$, of the experiment. The solid black line corresponds to a linear projection based upon data from $p \leq 0.75$, indicating the degree to which the data adhere to the expected utility prediction of linearity away from certainty.

The first question we ask is: are p and q in an exact linear relationship, as predicted

These results demonstrate consistency across elicitation techniques as higher elicited q and a higher number of safe HL choices both indicate more risk aversion.

by expected utility? To answer this we conducted a linear interval regression of q on p for only those $p \leq 0.75$, with a linear projection to $p = 1$. This is presented as the solid line in Figure 3. Figure 3 shows a clear pattern. The data fit the linear relationship extremely well for the bottom panel, the $(X, Y) = (10, 50)$ condition, but as we move up the linear fit begins to fail for probabilities of 0.90 and above, and becomes increasingly bad as p approaches certainty. In the $(10, 30)$ condition (top panel), EU fails to the point that the mean behavior violates stochastic dominance: the q for $p = 1$ is above the q for $p = 0.95$. Since q is a utility index for the p-gamble, this implies that a low outcome of \$10 for sure is worth more than a gamble with a 95 percent chance of \$10 and a 5 percent chance of \$30.

To explore the apparent non-linearity near $p = 1$, Table 1, Panels B and C present regression estimates of the relationship between q and p. Panel B estimates interval regressions assuming a quadratic relationship, and Panel C assumes a linear relationship. Expected utility is consistent with a square term of zero and S-shaped probability weighting is consistent with a negative square term. Panel B reveals a zero square term for the $(10, 50)$ condition, but positive and significant square terms for both $(30, 50)$ and $(10, 30)$ conditions.[23]

Our results are important for evaluating linearity-in-probabilities, and for understanding the robustness of the standard S-shaped weighting phenomenon. The data indicate that expected utility performs well away from certainty where the data adhere closely to linearity. However, the data deviate from linearity as p approaches 1, generating a convex relationship between p and q.

The regression analyses described above are complemented by non-parametric tests of concavity and convexity. These tests, introduced by Abrevaya and Jiang (2003,

[23]The parametric specifications of Panels B and C can be compared to the non-parametric specification presented in Panel A with simple likelihood ratio chi-square tests. Neither the quadratic nor the linear specification can be rejected relative to the fully non-parametric model: $\chi^2(15)_{A,B} = 8.23$, $(p = 0.91)$; $\chi^2(18)_{A,C} = 23.66$, $(p = 0.17)$. However, the linear specification of Panel C can be rejected relative to the parsimonious quadratic specification of Panel B, $\chi^2(3)_{B,C} = 15.43$, $(p < 0.01)$. We reject expected utility's linear prediction in favor of a convex relationship between p and q.

Table 1: Estimates of the Relationship Between q and p

	(1) $(X,Y)=(\$10,\$30)$	(2) $(X,Y)=(\$30,\$50)$	(3) $(X,Y)=(\$10,\$50)$
Dependent Variable: Interval Response of Uncertainty Equivalent ($q\times 100$)			
Panel A: Non-Parametric Estimates			
$p\times 100 = 10$	-3.623***	-2.575***	-3.869***
	(0.291)	(0.321)	(0.413)
$p\times 100 = 25$	-13.270***	-8.867***	-11.840***
	(0.719)	(0.716)	(0.748)
$p\times 100 = 50$	-24.119***	-13.486***	-22.282***
	(1.476)	(0.916)	(1.293)
$p\times 100 = 75$	-34.575***	-17.790***	-30.769***
	(2.109)	(1.226)	(1.777)
$p\times 100 = 90$	-39.316***	-19.171***	-36.463***
	(2.445)	(1.305)	(2.190)
$p\times 100 = 95$	-41.491***	-20.164***	-39.721***
	(2.635)	(1.411)	(2.425)
$p\times 100 = 100$	-41.219***	-21.747***	-43.800***
	(2.626)	(1.536)	(2.454)
Constant	95.298***	96.822***	96.230***
	(0.628)	(0.290)	(0.497)
	Log-Likelihood = -4498.66		
	AIC = -9047.32, BIC = 9185.02		
Panel B: Quadratic Estimates			
$p\times 100$	-0.660***	-0.376***	-0.482***
	(0.060)	(0.035)	(0.047)
$(p\times 100)^2$	0.002***	0.002***	0.001
	(0.001)	(0.000)	(0.000)
Constant	98.125***	97.855***	97.440***
	(0.885)	(0.436)	(0.642)
	Log-Likelihood = -4502.77		
	AIC = -9025.55, BIC = 9080.63		
Panel C: Linear Estimates			
$p\times 100$	-0.435***	-0.209***	-0.428***
	(0.027)	(0.016)	(0.027)
Constant	95.091***	95.603***	96.718***
	(0.678)	(0.512)	(0.714)
	Log-Likelihood = -4510.49		
	AIC = -9034.98, BIC = 9073.54		

Notes: Coefficients from single interval regression for each panel (Stewart, 1983) with 1823 observations. Standard errors clustered at the subject level in parentheses. 76 clusters. The regressions feature 1823 observations because one individual had a multiple switch point in one uncertainty equivalent in the $(X,Y)=(\$10,\$50)$ condition.

Level of significance: $^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

2005), develop non-parametric statistics constructed from examining the convexity or concavity of each combination of ordered triples $\{(p_1, q_1), (p_2, q_2), (p_3, q_3)\} \mid p_1 < p_2 < p_3$ for a given payment set (X, Y). If many more triples are convex relative to concave or linear, the underlying relationship is likely to be convex.[24]

The statistic, T_n, takes all combinations of potential triples in a set of data with n observations and counts the relative percentage of convex and concave triples. Appendix A.1 provides motivation and corresponding asymptotics for T_n, and simulates behavior and corresponding statistics. Clearly, the prediction for Expected Utility is that all triples are linear, so T_n should take value zero in each payment set. For S-shaped weighting the majority of triples are predicted to be concave. In our simulations of CPT, concave triples exceed convex triples by between 20 to 60 percentage points in our three payment sets.

We analyze the aggregate data by simply investigating the value of T_n estimated from the mean midpoint data in each payment set. In the series of 8 observations for each payment set, there are $\binom{8}{3} = 56$ potential ordered triples. For payment set $(X, Y) = (10, 30)$, we find $T_n(10, 30) = 0.89$, such that the percentage of convex triples in the mean data exceed the percentage of concave triples by almost 90 percentage points. Appendix A.1 discusses the construction of hypothesis tests following Abrevaya and Jiang (2003, 2005). For the mean data, we reject the null hypothesis of linearity at all conventional levels ($z = 13.8,\ p < 0.01$). Likewise for the mean data in payment set $(X, Y) = (30, 50)$, we find $T_n(30, 50) = 0.50$ and we again reject the null hypothesis of linearity ($z = 3.0,\ p < 0.01$). For the mean data in payment set $(X, Y) = (10, 50)$, we find $T_n(10, 50) = 0.04$, echoing the near linearity observed in Table 1 Panel B, and we fail to reject the null hypothesis of linearity ($z = 0.14,\ p = 0.44$).

The analysis of this sub-section generates two results. First, expected utility performs well away from certainty. Second, at certainty behavior deviates from expected

[24] The relevant comparison is whether $\frac{q_2 - q_1}{p_2 - p_1}$ is greater than, less than or equal to $\frac{q_3 - q_2}{p_3 - p_2}$. See Appendix A.1 for further detail.

utility in a surprising way, rejecting standard notions of Cumulative Prospect Theory. The aggregate relationship, uncovered both non-parametrically and with regressions, is convex. This result is in contrast to the linear prediction of expected utility and the concave prediction of S-shaped probability weighting.

4.2 Certainty Equivalents Data

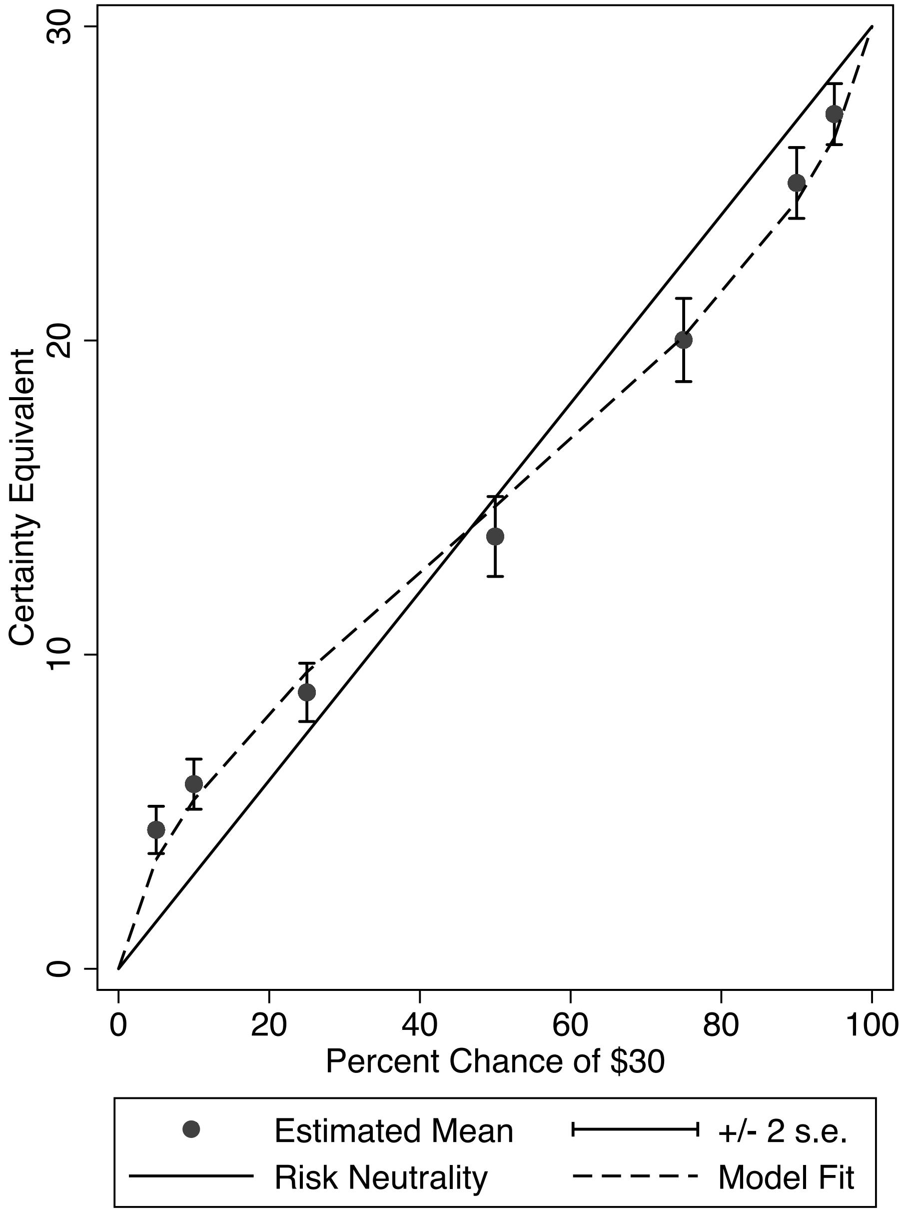
The data from our uncertainty equivalents environment are in contrast to a standard S-shaped weighting account of deviations from expected utility. Given that uncertainty equivalents are a minor deviation from the standard certainty equivalent environment in which S-shaped weighting is robustly produced, this may come as a surprise. However, we cannot tell if our subjects are an unusual selection. In this subsection we examine standard certainty equivalents and document that our sample reproduces evidence of S-shaped weighting.

Seven certainty equivalents tasks with p gambles over \$30 and \$0 from the set $p \in \{0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95\}$ were administered, following the probabilities used in the original probability weighting experiments of Tversky and Kahneman (1992) and Tversky and Fox (1995). The analysis also follows closely the presentation and non-linear estimation techniques of Tversky and Kahneman (1992) and Tversky and Fox (1995).

Figure 4 presents a summary of the certainty equivalents.[25] As in sub-section 4.1, we first conducted an interval regression of the certainty equivalent, C, on indicators for the experimental probabilities. Following Tversky and Kahneman (1992), the data are presented relative to a benchmark of risk neutrality such that, for a linear utility function, Figure 4 directly reveals the probability weighting function, $\pi(p)$. The data show evidence of S-shaped probability weighting. Subjects appear significantly

[25] Figure 4 excludes one subject with multiple switching in one task. Identical aggregate results are obtained with the inclusion of this subject. However, we cannot estimate probability weighting at the individual level for this subject.

Figure 4: Certainty Equivalent Responses



Note: Mean certainty equivalent response. Solid line corresponds to risk neutrality. Dashed line corresponds to fitted values from non-linear least squares regression (1).

risk loving at low probabilities and significantly risk averse at intermediate and high probabilities. These findings are in stark contrast to those obtained in the uncertainty equivalents discussed in Section 4.1. Whereas in uncertainty equivalents we obtain no support for S-shaped probability weighting, in certainty equivalents we reproduce the probability weighting results generally found.[26]

Tversky and Kahneman (1992) and Tversky and Fox (1995) obtain probability weighting parameters from certainty equivalents data by parameterizing both the utility and probability weighting functions and assuming the indifference condition

$$u(C) = \pi(p) \cdot u(30)$$

is met for each observation. We follow the parameterization of Tversky and Kahneman (1992) with power utility, $u(X) = X^{\alpha}$, and the one-parameter weighting function $\pi(p) = p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}$.[27] Lower γ corresponds to more intense probability weighting. The parameters $\hat{\gamma}$ and $\hat{\alpha}$ are then estimated as the values that minimize the sum of squared residuals of the non-linear regression equation

$$C = [p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma} \times 30^{\alpha}]^{1/\alpha} + \epsilon. \tag{1}$$

When conducting such analysis on our aggregate data with standard errors clustered on the subject level, we obtain $\hat{\alpha} = 1.07$ (0.05) and $\hat{\gamma} = 0.73$ (0.03).[28] The hypothesis of linear utility, $\alpha = 1$, is not rejected, ($F_{1,74} = 2.18,\ p = 0.15$), while linearity in probability, $\gamma = 1$, is rejected at all conventional levels, ($F_{1,74} = 106.36,\ p < 0.01$). The model fit is presented as the dashed line in Figure 4. The obtained probability weighting estimate compares favorably with the Tversky and Kahneman (1992) estimate of $\hat{\gamma} =$

[26]Certainty equivalents correlate significantly with the number of safe choices in the Holt-Laury risk tasks. For example, for $p = 0.5$ the individual correlations between the midpoint certainty equivalent, C, and the number of safe choices, S_{10} and S_{30}, in the HL tasks are $\rho_{C,S_{10}} = -0.24$ ($p < 0.05$) and $\rho_{C,S_{30}} = -0.24$ ($p < 0.05$). These results demonstrate consistency across elicitation techniques as a lower certainty equivalent and a higher number of safe HL choices both indicate more risk aversion. Additionally, the certainty equivalents correlate significantly with uncertainty equivalents. For example, for $p = 0.5$ the individual correlations between the midpoint certainty equivalent, C, and the midpoint of the uncertainty equivalent, q, are $\rho_{C,q(10,30)} = -0.24$ ($p < 0.05$), $\rho_{C,q(30,50)} = -0.25$ ($p < 0.05$), and $\rho_{C,q(10,50)} = -0.24$ ($p < 0.05$).

[27]Tversky and Fox (1995) use power utility with curvature fixed at $\alpha = 0.88$ from Tversky and Kahneman (1992) and a two parameter $\pi(\cdot)$ function.

[28]For this analysis we estimate using the interval midpoint as the value of C, and note that the dependent variable is measured with error.

0.61 and other one-parameter estimates such as Wu and Gonzalez (1996) who estimate $\hat{\gamma} = 0.71$.

The findings of this sub-section indicate that our subjects are not selected on a specific shape of risk preference. Though they fail to adhere to the S-shaped weighting model in their uncertainty equivalent behavior, our subjects closely reproduce prior findings of prospect theoretic shapes in the traditional certainty equivalent environment.

The uncertainty equivalent is motivated as an experimental environment where the shape of probability distortions can be identified without confounds, while the identification of probability weighting from certainty equivalents discussed above clearly depends on the specification of utility in (1). In the following individual analysis subsection we investigate the link between our two experimental environments, drawing an interesting correlation between violations of stochastic dominance in our uncertainty equivalents and the identification of prospect theory shapes in our certainty equivalents.

4.3 Individual Analysis: Dominance Violations and Probability Weighting

A substantial portion of our subjects violate first order stochastic dominance in their uncertainty equivalent behavior. These violations are organized close to $p = 1$. Since the q elicited in an uncertainty equivalent acts as a utility index, dominance violations are identified when a subject reports a higher q for a higher p, indicating that they prefer a greater chance of a *smaller* prize.

Each individual has 84 opportunities to violate first order stochastic dominance in such a way.[29] We can identify the percentage of choices violating stochastic dominance

[29]Identifying violations in this way recognizes the interval nature of the data as it is determined by price list switching points. We consider violations within each payment set (X, Y). With 8 probabilities in each set, seven comparison can be made for $p = 1 : p' \in \{0.95, 0.9, 0.75, 0.5, 0.25, 0.1, 0.05\}$. Six comparisons can be made for $p = 0.95$ and so on, leading to 28 comparisons for each payment set and 84 within-set comparisons of this form.

at the individual level and so develop an individual violation rate. To begin, away from certainty, violations of stochastic dominance are few, averaging only 4.3% ($s.d. =$ 6.4%). In the 21 cases per subject when certainty, $p = 1$, is involved, the individual violation rate increases significantly to 9.7% (15.8%), ($t = 3.88,\ p < 0.001$). When examining only the three comparisons of $p = 1$ to $p' = 0.95$, the individual violation rate increases further to 17.5% (25.8%), ($t = 3.95,\ p < 0.001$). Additionally, 38 percent (29 of 76) of subjects demonstrate at least one violation of stochastic dominance when comparing $p = 1$ to $p' = 0.95$. This finding suggests that violations of stochastic dominance are prevalent and tend to be localized close to certainty.

To simplify discussion, we will refer to individuals who violate stochastic dominance between $p = 1$ and $p' = 0.95$ as *Violators*. The remaining 62 percent of subjects are classified as *Non-Violators*.[30]

Our finding of *within-subject* violations of stochastic dominance is evidence of the hotly debated 'uncertainty effect.' Gneezy et al. (2006) discuss between-subject results indicating that a gamble over book-store gift certificates is valued less than the certainty of the gamble's worst outcome. Though the effect was reproduced in Simonsohn (2009), other work has challenged these results (Keren and Willemsen, 2008; Rydval et al., 2009). While Gneezy et al. (2006) do not find within-subject examples of the uncertainty effect, Sonsino (2008) finds a similar within-subject effect in the Internet auction bidding behavior of around 30% of individuals. Additionally, the uncertainty effect was thought not to be present for monetary payments (Gneezy et al., 2006). Our findings may help to inform the debate on the uncertainty effect and its robustness to the monetary domain. Additionally, our results may also help to identify the source of the uncertainty effect. In the following discussion we demonstrate that models which

[30]There were no session or order effects obtained for stochastic dominance violation rates or categorization of Violators. Violators are also more likely to violate stochastic dominance away from certainty. Their violation rate away from certainty is 8.2% (7.5%) versus 1.9% (4.1%) for Non-Violators, ($t = 4.70,\ p < 0.001$). This, however, is largely driven by violations close to certainty.

feature direct preferences for certainty, such as disappointment aversion or u-v preferences, predict the observed violations of dominance at certainty. Indeed, something close to the intuition of direct certainty preferences is hypothesized by Gneezy et al. (2006), who argue that "an individual posed with a lottery that involves equal chance at a $50 and $100 gift certicate might code this lottery as a $75 gift certicate plus some risk. She might then assign a value to a $75 gift certicate (say $35), and then reduce this amount (to say $15) to account for the uncertainty."[p. 1291]

It is important to note that the violations of stochastic dominance that we document are indirect measures of violation. We hypothesize that violations of stochastic dominance would be less prevalent in direct preference rankings of gambles with a dominance relation. Though we believe the presence of dominance violations can be influenced by frames, this is likely true for the presence of many decision phenomena.

Table 2: Estimated Probability Weighting and Uncertainty Equivalent Behavior

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: $\hat{\gamma}_i$					
Violator (= 1)	-0.113*	-0.167***				
	(0.059)	(0.060)				
$p = 1$ vs. $p = 0.95$ Violation Rate			-0.264**	-0.300***		
			(0.103)	(0.105)		
$p = 1$ vs. $p < 1$ Violation Rate					-0.520**	-0.707***
					(0.197)	(0.165)
Constant	0.864***	0.863***	0.867***	0.857***	0.871***	0.869***
	(0.045)	(0.046)	(0.042)	(0.043)	(0.040)	(0.042)
Trimmed Sample	No	Yes	No	Yes	No	Yes
R-Squared	0.042	0.081	0.064	0.082	0.094	0.141
N	74	67	74	67	74	67

Notes: Coefficients from ordinary least squares regression with robust standard errors in parentheses. Columns (1), (3), (5), estimate effects for the full sample: 74 individuals with complete data. Columns (2), (4), (6), estimate effects for the restricted sample with more precisely estimated probability weighting parameters. Restricted sample is 10% trim of the estimated $s.e.(\hat{\gamma}_i)$ yielding 67 individuals.

Level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

The puzzling behavior of violating dominance near p equal to 1 in our uncertainty equivalents is closely linked to the exhibiting probability weighting behavior in our certainty equivalents. That is, violations of first order stochastic dominance have predictive power for the standard prospect theoretic shapes.

Assuming linear utility, $\alpha = 1$, we estimate (1) for each individual based on the midpoints of their certainty equivalent responses to obtain an individual probability weighting estimate, $\hat{\gamma}_i$.[31] For the 74 (of 76) individuals with complete certainty equivalent and uncertainty equivalent data, we estimate a mean $\hat{\gamma}_i$ of 0.819 ($s.d. = 0.272$). However, a number of subjects have parameter values estimated with limited precision. While the mean standard error $s.e.(\hat{\gamma}_i)$ is 0.124, 10% of subjects have standard errors in excess of 0.25, limiting our ability to make unmuddied inference as to the extent of their implied probability weighting.

In Table 2 we link the estimated probability weighting in certainty equivalents to the observed behavior in the uncertainty equivalents. In column (1) we correlate the extent of S-shaped weighting with whether individuals violate first order stochastic dominance in the uncertainty equivalents, Violator (= 1). In column (2) we conduct a 10% trim of $s.e.(\hat{\gamma}_i)$, allowing us to focus on those individuals with more precisely identified values of $\hat{\gamma}_i$. Though a limited correlation is obtained in column (1), under the 10% trim of column (2), we document that violators of first order stochastic dominance have significantly lower values of $\hat{\gamma}_i$. Interestingly, the point estimate has clear economic import. Individuals who violate stochastic dominance at certainty have estimated probability weighting parameters -0.2 below Non-Violators. Violators drive the nonlinearity in probabilities.

To further investigate the relationship between violating stochastic dominance and estimated probability weighting, columns (3) through (6) use alternate measures of dominance violation. Columns (3) and (4) use the Violation Rate between $p = 1$ and

[31] We motivate the assumption of $\alpha = 1$ with the near linear utility estimated in the aggregate data. A similar exercise is conducted by Tversky and Fox (1995) who fix $\alpha = 0.88$ and estimate probability weighting at the individual level. Attempting to estimate both $\hat{\alpha}$ and $\hat{\gamma}$ based on seven observations per subject yields extreme estimates in some cases.

$p = 0.95$ as a continuous measure for the likelihood of exhibiting a dominance violation close to certainty. Columns (5) and (6) use the Violation Rate between $p = 1$ and all lower probabilities, such that a higher violation rate indicates a more intense kink at certainty. Again, we document that individuals that violate stochastic dominance and do so more intensely have lower estimated values of $\hat{\gamma}_i$. S-shaped probability weighting as identified in standard certainty equivalents experiments correlates highly with violating first order stochastic dominance in our uncertainty equivalents.

In the following discussion we provide an initial, but far from conclusive exercise attempting to find a unifying framework for understanding our results.

5 Discussion

Our analysis demonstrates three critical findings. First, in an experimental environment where unconfounded inference can be made as to the shape of probability distortions, no support for S-shaped probability weighting is obtained. Rather, a number of individuals exhibit a surprising preference for certainty, violating dominance near p equal to 1. Second, in contrast to the 1st result, in standard certainty equivalents evidence of S-shaped weighting is obtained. Third, these disparate findings appear to be linked by individuals who exhibit violations of first order stochastic dominance. Attempting to understand these linkages is the purpose of this discussion.

Our results are not easily explained by the potentially attractive view of interpreting dominance violations as a mistake and S-shaped probability weighting as a preference (or vice versa) as the two behaviors correlate significantly at the individual level. Additionally, it is beyond the scope of this paper to definitively answer the question of whether the observed behavior and correlation is rooted in a common preference or a common decision error. However, we do provide an initial suggestive exercise indicating that models with direct preferences for certainty as in disappointment aversion and u-v preferences can generate both the convex shape and dominance violations of our uncertainty equivalents, especially if there are small decision or measurement errors, and at least partially account for the observed probability weighting in our certainty equivalents. This exercise suggests that probability weighting, as identified in estimation from certainty equivalents may be a product of specification error.

To begin, we demonstrate that both u-v preferences and disappointment aversion can generate a convex relationship between assessment gambles and their corresponding uncertainty equivalents as well as dominance violations close to probability 1.

First, the u-v model (Neilson, 1992; Schmidt, 1998; Diecidue et al., 2004) is designed to capture Allais' (1953b) intuition of a disproportionate preference for security in the 'neighborhood of certainty.' The model adheres to expected utility away from certainty, but certain outcomes are evaluated with a separate utility function. Let $u(X)$ be the utility of $\$X$ with uncertainty and $v(X)$ be the utility of $\$X$ with certainty. Assume $v(X) > u(X)$ for $\$X > 0$. Under such u-v preferences, p and q will have a linear relationship away from $p = 1$. At $p = 1$, the discontinuity in utility introduces a discontinuity in the relationship between p and q. At $p = 1$, the q that solves the indifference condition

$$v(X) = q \cdot u(Y)$$

will be

$$q = \frac{v(X)}{u(Y)} > \frac{u(X)}{u(Y)}.$$

With the u-v specification, q will be linearly decreasing in p and then discontinuously *increase* at $p = 1$. This discontinuity introduces two characteristics to the relationship between p and q. First, though the data are linear away from certainty, the discontinuity will generate an overall convexity to the relationship. Second, the increase in q at certainty of a low outcome corresponds to violations of first order stochastic dominance. As with the other models, in Appendix A.1 we simulate data in our experimental environment for u-v decision-makers. We demonstrate a substantially convex relationship between q and p, confirmed by both non-parametric and regression-based tests, and potential violations of first order stochastic dominance.

Next, we consider disappointment aversion, referring to a broad class of reference-dependent models where a gamble's outcomes are evaluated relative to the gamble's EU certainty equivalent (Bell, 1985; Loomes and Sugden, 1986; Gul, 1991). Take a p chance of $\$X$ and a $1-p$ chance of a larger payment $\$Y > \$X$. The certainty equivalent of this prospect is the value, C_p, satisfying $p \cdot u(X) + (1-p) \cdot u(Y) = u(C_p)$. Taking C_p as the reference point, the reference-dependent utility of the p-gamble is then

$$p \cdot \tilde{u}(X|C_p) + (1-p) \cdot \tilde{u}(Y|C_p)$$

where $\tilde{u}(\cdot|C_p)$ is the reference-dependent utility function with reference point C_p.

We assume a standard specification for $\tilde{u}(\cdot|C_p)$ (Bell, 1985; Loomes and Sugden, 1986),

$$\tilde{u}(z|C_p) = u(z) + \mu(u(z) - u(C_p)),$$

where the function $u(z)$ represents consumption utility for some outcome, z, and $\mu(\cdot)$ represents disappointment-elation utility relative to the referent, C_p. Several simplifying assumptions are made. We assume a piecewise-linear disappointment-elation function,

$$\mu(u(z) - u(C_p)) = \left\{ \begin{array}{lll} \eta \cdot (u(z) - u(C_p)) & if & u(z) - u(C_p) \geq 0 \\ \eta \cdot \lambda \cdot (u(z) - u(C_p)) & if & u(z) - u(C_p) < 0 \end{array} \right\},$$

where the utility parameter $\eta > 0$ represents the sensitivity to disappointment and elation and λ captures the degree of disappointment aversion. $\lambda > 1$ indicates disappointment aversion.

When considering certainty, there is no prospect of disappointment. This leads individuals with $\lambda > 1$ to be more risk averse at $p = 1$ than away from $p = 1$. In effect, this is what we term a preference for certainty in models of disappointment aversion. The changing pattern of risk aversion moving towards certainty predicts a convex shape to the relationship between $(p; X, Y)$ gambles and their uncertainty equivalents, $(q; Y, 0)$, and can, at specific parameter values, generate violations of first order stochastic dominance at certainty.

Because the reference point depends on the gamble under consideration, utility depends non-linearly on probabilities. Under the formulation above, the disappointment averse utility of the gamble $(p; X, Y)$ is

$$U_p = p \cdot [u(X) + \lambda\eta \cdot (u(X) - u(C_p))] + (1-p) \cdot [u(Y) + \eta \cdot (u(Y) - u(C_p))].$$

or

$$U_p = [p + p(1-p)\eta(\lambda - 1)]u(X) + [(1-p) - p(1-p)\eta(\lambda-1)]u(Y).$$

Defining

$$\tilde{\pi}(1-p) \equiv [(1-p) - p(1-p)\eta(\lambda-1)],$$

we find

$$U_p = [1 - \tilde{\pi}(1-p)] \cdot u(X) + \tilde{\pi}(1-p) \cdot u(Y).$$

Note that this implies that for two outcome gambles as in the uncertainty equivalent, disappointment aversion is observationally equivalent to a form of CPT with the specific weighting function, $\tilde{\pi}(1-p)$. In addition $\tilde{\pi}(1-p) \leq 1-p$ if $\lambda > 1$, and $\tilde{\pi}(1-p)$ is a convex function describing a parabola with critical point $1-p = (\eta(\lambda-1)-1)/2\eta(\lambda-1)$.

Following identical logic to the development of S-shaped weighting, the uncertainty equivalent indifference relation again implies

$$\frac{dq}{dp} = -\frac{\tilde{\pi}'(1-p)}{\tilde{\pi}'(q)} \cdot [1-\theta].$$

Because the weighting function, $\tilde{\pi}(\cdot)$, is convex, one can easily check that the second derivative, $\frac{d^2q}{dp^2}$, is greater than zero, implying that disappointment aversion predicts a convex relationship between p and q for $\lambda > 1$.[32]

As p approaches 1, $\tilde{\pi}'(1-p)$ approaches $1 + \eta - (\eta\lambda)$ under our formulation. For sufficiently disappointment averse individuals ($\lambda > (1+\eta)/\eta$ in this example) the relationship between p and q will become positive as p approaches 1, provided $\tilde{\pi}'(q) > 0$. This is an important prediction of disappointment aversion. A positive relationship between p and q near certainty implies violations of first order stochastic dominance as certainty is approached.

Importantly, some disappointment averse models are constructed with assumptions guaranteeing that the underlying preferences satisfy stochastic dominance (Loomes and Sugden, 1986; Gul, 1991), while others are not (Bell, 1985). However, identification based on this distinction will not be fruitful as they are written to be deterministic models of decision-making. With decision error, all such models would likely predict dominance violations at some parameter values. Hence, we view violations of domi-

[32]We assume $q \geq 1-p$. Convexity implies $\tilde{\pi}'(q) \geq \tilde{\pi}'(1-p)$. For the employed specification $\tilde{\pi}'(1-p) = 1-\eta(\lambda-1)+2(1-p)\eta(\lambda-1)$ and $\tilde{\pi}''(\cdot)$ is a constant, such that $\tilde{\pi}''(1-p) = \tilde{\pi}''(q) = 2\eta(\lambda-1)$. This second derivative is positive under the assumption $\lambda > 1$. Hence, the sign of

$$\frac{d^2q}{dp^2} = \frac{\tilde{\pi}''(1-p)\cdot[1-\theta]\cdot\tilde{\pi}'(q) + \tilde{\pi}''(q)\frac{dq}{dp}\cdot\tilde{\pi}'(1-p)\cdot[1-\theta]}{\tilde{\pi}'(q)^2}.$$

depends on the sign of

$$\tilde{\pi}'(q) + \frac{dq}{dp}\cdot\tilde{\pi}'(1-p).$$

Plugging in for dq/dp

$$\tilde{\pi}'(q) - \frac{\tilde{\pi}'(1-p)}{\tilde{\pi}'(q)}\cdot[1-\theta]\cdot\tilde{\pi}'(1-p),$$

and dividing by $\tilde{\pi}'(q)$ we obtain

$$1 - \frac{\tilde{\pi}'(1-p)}{\tilde{\pi}'(q)}\cdot[1-\theta]\cdot\frac{\tilde{\pi}'(1-p)}{\tilde{\pi}'(q)}.$$

Because convexity of $\tilde{\pi}(\cdot)$ and $q \geq (1-p)$ implies $\tilde{\pi}'(q) \geq \tilde{\pi}'(1-p)$, $\tilde{\pi}'(1-p)/\tilde{\pi}'(q) \leq 1$. Additionally $1-\theta < 1$, by the assumption of monotonicity. The second term is therefore a multiplication of three terms that are less than or equal to 1 and one concludes

$$1 - \frac{\tilde{\pi}'(1-p)}{\tilde{\pi}'(q)}\cdot[1-\theta]\cdot\frac{\tilde{\pi}'(1-p)}{\tilde{\pi}'(q)} > 0,$$

$d^2q/dp^2 > 0$, the relationship is convex.

nance at p equal to 1 as indicative of a preference for certainty and not as a criterion for restricting among the class of models with such a preference.

As with the other models, in Appendix A.1 we simulate data in our experimental environment for disappointment averse decision-makers. We demonstrate a substantially convex relationship between q and p under disappointment aversion, confirmed by both non-parametric and regression-based tests, as well as the potential for violations of stochastic dominance near certainty.

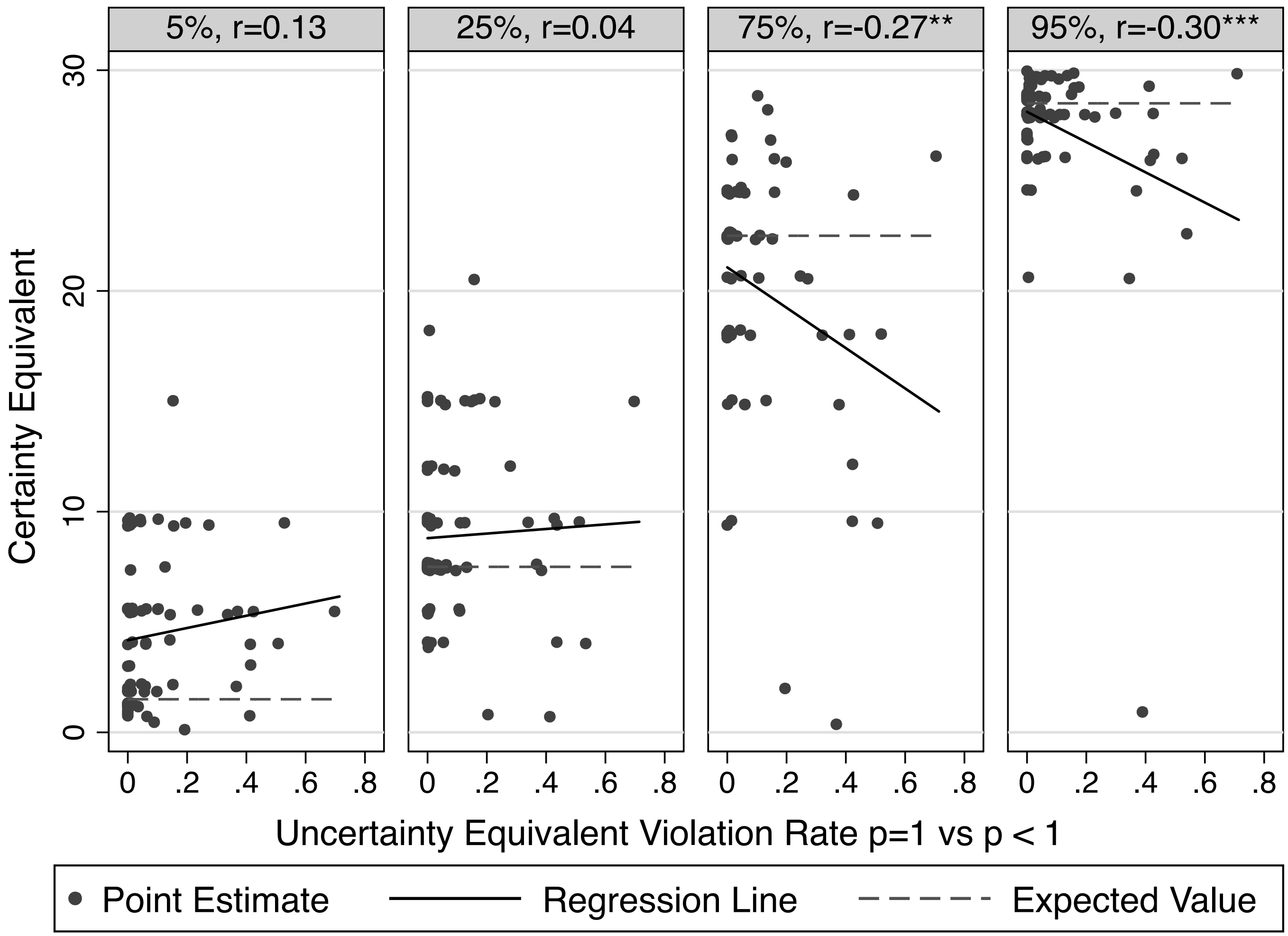
Models with specific preferences for certainty, such as disappointment aversion and u-v preferences, yield the convex shapes obtained in our uncertainty equivalent environment as well as the prevalence of dominance violations near to certainty. The next question we ask is how would an individual with such preferences behave in a certainty equivalent? If certainty is disproportionately preferred, certainty equivalent measures will overstate the level of risk aversion. If then the specific functional forms of S-shaped weighting are fit to the data, this leads to a misspecification as the preference for certainty confounds the identification of non-linearities in probabilities.

We investigate this claim in the four panels of Figure 5. The potential preference for certainty is taken as the Violation Rate between $p = 1$ and $p < 1$.[33] This measure is correlated with the certainty equivalent responses for gambles offering a 5% , 25% , 75% and 95% chance of receiving \$30.[34] Corresponding to the prediction, individuals with a potentially more intense preference for certainty are significantly more risk averse for

[33] This measure is designed to capture the intensity of the preference for certainty as individuals that are more disappointment averse (i.e larger λ) or have greater direct preferences for certainty should violate dominance in a greater proportion of choices than those that are less so. We recognize that this is a rough measure of intensity of certainty preference in the sense that individuals could have a non-monotonic relationship between p and q away from certainty. However, given the low dominance violation rates away from certainty, this is not overly problematic. A small minority of Non-Violators have non-zero $p = 1$ vs $p < 1$ violation rates, as their elicited q at certainty is higher than that of some lower probability. The average $p = 1$ vs $p < 1$ violation rate (0.069) for the 19% of Non-Violators (9 of 47) with positive values is about same as their average violation rate away from certainty (0.060). For Violators, the average $p = 1$ vs $p < 1$ violation rate (0.235) is about three times their violation rate away from certainty (0.082).

[34] Certainty equivalents are measured as the midpoint of the interval implied by an individual's switch point in a given certainty equivalent task.

Figure 5: Certainty Equivalents for 5%, 25%, 75% and 95% chance of $30 and Uncertainty Equivalent $p = 1$ vs $p < 1$ Violation Rate



Note: Correlation coefficients (r) for 74 of 76 subjects. Two subjects with multiple switching not included. One percent jitter added to scatter plots. Two observations with Violation Rate = 0 and $\hat{\gamma}_i \geq 2$ not included in scatter plots, but included in regression line and reported correlation. *Level of significance*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the higher probability gambles, with correlation coefficients, r, ranging from 0.27, ($p < 0.05$) to 0.30, ($p < 0.01$). Insignificant positive correlations are found at lower probabilities. For subjects with a more intense preference for certainty, the significant increase in risk aversion at high probabilities (and the null effects at lower probabilities) introduces more non-linearity into their estimated probability weighting functions. As documented in Table 2, Columns (5) and (6) individuals with higher values of $p = 1$ vs. $p < 1$ Violation Rate have substantially and significantly more non-linear estimated probability weighting functions. Of course, it should be stated that because the predictions of disappointment aversion and u-v preferences are global, one cannot easily accommodate the average finding of risk loving behavior at low probabilities. Hence, direct preferences for certainty can give only a partial account of our certainty equivalent data.

Models with direct preferences for certainty can rationalize the pattern of behavior observed in the uncertainty equivalent data and at least partially account for the certainty equivalent elicited probability weighting and the linkage between prospect theoretic shapes and dominance violations. Further, this suggests that behavior in certainty equivalents often attributed to S-shaped weighting may be the product of a misspecification combined with direct preferences for certainty. Standard estimation exercises assuming functional form for utility or probability weighting cannot be used to directly test linearity-in-probabilities. Though the exercise we reported in this section is meant only to provide some direction and intuition, it is nonetheless clear that if people carry specific preferences for certainty then certainty based experiments may yield non-expected utility behavior. In particular, the certainty effects Allais described would be built into the experimental design.

To add to the puzzle, there exist a number of studies parametrically investigating probability weighting in decisions without certainty (Tanaka, Camerer and Nguyen, 2010; Booij, van Praag and van de Kuilen, 2010). These parametric estimates indicate that S-shaped probability weighting may be observed in decisions without certainty and clearly points to the need for future research. Additionally, attention must be given to the 'parameter-free' elicitation techniques that find non-parametric support for non-linear probability weights (Gonzalez and Wu, 1999; Abdellaoui, 2000; Bleichrodt and Pinto, 2000). Importantly, both Gonzalez and Wu (1999) and Abdellaoui (2000) make use of certainty equivalents or at least a number of certain outcomes to identify probability weights, a technique that is misspecified if there exists a specific preference for certainty.[35] Bleichrodt and Pinto (2000) do not use certainty equivalents techniques, but their experiment is designed not to elicit preferences over monetary payments, but rather over hypothetical life years.[36]

In sum our results suggest that a direct preference for certainty is likely to play some role in reconsidering the large body of research on models of risk.

6 Conclusion

Volumes of research exists exploring both the implications and violations of the independence axiom. Surprisingly, little research exists directly testing the most critical result of the independence axiom: linearity-in-probabilities of the Expected Utility (EU) function. We present an experimental device that easily generates such a direct test, the *uncertainty equivalent*. Uncertainty equivalents not only provide tests of expected utility's linearity-in-probabilities, but also provides a methodology for testing alternative preference models such as Cumulative Prospect Theory's (CPT) inverted S-

[35] Abdellaoui (2000) makes use of the trade-off method of Wakker and Deneffe (1996) for elicitation of the utility function and apparently used certainty equivalents for the elicitation of the probability equivalent. Though we cannot be certain, the experiment is described as follows "In the PW [Probability Weighting]-experiments, each subject was asked a new series of choice questions to determine the probabilities $p_1, ..., p_5$ that make her indifferent between the outcome x_i and the prospect $(x_6, p_i, x_0), i = 1, ..., 5$" (page 1504).

[36] Abdellaoui (2000), Bleichrodt and Pinto (2000), Booij and van de Kuilen (2009) and Booij et al. (2010) share a two-stage elicitation procedure which 'chains' responses in order to obtain utility or probability weighting values. Such chained procedures are common to the 'trade-off' (Wakker and Deneffe, 1996) method of utility assessment. A discussed problem with these chained methods is that errors propagate through the experiment.

shaped probability weighting (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) without assumptions for the functional form of utility.

In a within-subject experiment with both uncertainty equivalents and standard certainty equivalent methodology we demonstrate a series of important results. First, independence performs well away from certainty where probabilities are found to be weighted nearly linearly. Second, independence breaks down close to certainty. The nature of the violation is contrary to standard S-shaped probability weighting. Third, in certainty equivalents these same subjects reproduce with precision the standard finding of S-shaped weighting. These apparently disparate results are linked by a puzzling fact. Nearly 40% of subjects indirectly violate first order stochastic dominance as probabilities approach 1 in our uncertainty equivalents. Such individuals are substantially more likely to exhibit the hallmarks of S-shaped weighting in their certainty equivalent behavior.

We show that models with specific preferences for certainty are able to rationalize the pattern of behavior in the uncertainty equivalents and explain the linkage between violations of dominance and certainty equivalent-elicited probability weighting. This suggests that empirical work should take great care to separate certainty preferences from other phenomena under investigation. Additionally, theoretical research should take seriously models with specific preferences for certainty, (small scale) violations of stochastic dominance, and their implications for decision-making under uncertainty.

References

Abdellaoui, Mohammed, "Parameter-Free Elicitation of Utility and Probability Weighting Functions," *Management Science*, 2000, *46* (11), 1497–1512.

Abrevaya, Jason and Wei Jiang, "Pairwise-Slopes Statistics for Testing Curvature," *Working Paper*, 2003.

_ **and** _ , "A Nonparametric Approach to Measuring and Testing Curvature," *Journal of Business and Economic Statistics*, 2005, *23* (1), 1–19.

Allais, Maurice, "Fondements d'une Thèorie Positive des Choix Comportant un Risque," in "Colloques Internationaux du Centre Natlonal de la Recherche Scientifique (Econometrie) 40" 1953, pp. 127–140.

_ , "Le Comportement de l'Homme Rationnel devant le Risque: Critique des Postulats et Axiomes de l'Ecole Americaine," *Econometrica*, 1953, *21* (4), 503–546.

Andreoni, James and Charles Sprenger, "Risk Preferences Are Not Time Preferences," *Working Paper*, 2011.

Bell, David E., "Disappointment in Decision Making under Uncertainty," *Operations Research*, 1985, *33* (1), 1–27.

Bernouilli, Daniel, "Specimen Theoriae Novae de Mensura Sortis," *Commentarii Academiae Scientiarum Imperialis Petropolitanae*, 1738, *5*, 175–192.

Bleichrodt, Han and Jose Luis Pinto, "A Parameter-Free Elicitation of the Probability Weighting Function in Medical Decision Analysis," *Management Science*, 2000, *46* (11), 1485–1496.

_ **, Jose Maria Abellan-Perinan, Jose Luis Pinto-Prades, and Ildefonso Mendez-Martinez**, "Resolving Inconsistencies in Utility Measurment Under Risk: Tests of Generalizations of Expected Utility," *Management Science*, 2007, *53* (3).

Booij, Adam S. and Gijs van de Kuilen, "A Parameter-Free Analysis of the Utility of Money for the General Population Under Prospect Theory," *Journal of Economic Psychology*, 2009, *30*, 651–666.

_ **, Bernard M. S. van Praag, and Gijs van de Kuilen**, "A Parametric Analysis of Prospect Theory's Functionals for the General Population," *Theory and Decision*, 2010, *68*, 115–148.

Camerer, Colin F., "Recent Tests of Generalizations of Expected Utility Theory," in Ward Edwards, ed., *Utility: Theories, Measurement, and Applications*, Kluwer: Norwell, MA, 1992, pp. 207–251.

Conlisk, John, "Three Variants on the Allais Example," *The American Economic Review*, 1989, *79* (3), 392–407.

Cubitt, Robin P., Chris Starmer, and Robert Sugden, "On the Validity of the Random Lottery Incentive System," *Experimental Economics*, 1998, *1*, 115–131.

Diecidue, Enrico, Ulrich Schmidt, and Peter P. Wakker, "The Utility of Gambling Reconsidered," *Journal of Risk and Uncertainty*, 2004, *29* (3), 241–259.

Epstein, Larry G. and Stanley E. Zin, "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework," *Econometrica*, 1989, *57* (4), 937–969.

Farquhar, Peter H., "Utility Assessment Methods," *Management Science*, 1984, *30* (11), 1283–1300.

Fishburn, Peter and Peter Wakker, "The Invention of the Independence Condition for Preferences," *Management Science*, 1995, *41* (7), 1130–1144.

Gneezy, Uri, John A. List, and George Wu, "The Uncertainty Effect: When a Risky Prospect Is Valued Less Than Its Worst Possible Outcome," *The Quarterly Journal of Economics*, 2006, *121* (4), 1283–1309.

Gonzalez, Richard and George Wu, "On the Shape of the Probability Weighting Function," *Cognitive Psychology*, 1999, *38*, 129–166.

Gul, Faruk, "A Theory of Disappointment Aversion," *Econometrica*, 1991, *59* (3), 667–686.

Harless, David W. and Colin F. Camerer, "The Predictive Utility of Generalized Expected Utility Theories," *Econometrica*, 1994, *62* (6), 1251–1289.

Harrison, Glenn W. and Elisabet E. Rutstrom, "Risk Aversion in the Laboratory," in Glenn W. Harrison and James C. Cox, eds., *Research in Experimental Economics: Volume 12. Risk Aversion in Experiments*, Bingley: Emeraled, 2008.

_ , Morten I. Lau, Elisabet E. Rutstrom, and Melonie B. Williams, "Eliciting risk and time preferences using field experiments: Some methodological issues," in Jeffrey Carpenter, Glenn W. Harrison, and John A. List, eds., *Field experiments in economics*, Vol. Vol. 10 (Research in Experimental Economics), Greenwich and London: JAI Press, 2005.

Hey, John D. and Chris Orme, "Investigating Generalizations of Expected Utility Theory Using Experimental Data," *Econometrica*, 1994, *62* (6), 1291–1326.

Holt, Charles A. and Susan K. Laury, "Risk Aversion and Incentive Effects," *The American Economic Review*, 2002, *92* (5), 1644–1655.

Jacobson, Sarah and Ragan Petrie, "Learning from Mistakes: What Do Inconsistent Choices Over Risk Tell Us?," *Journal of Risk and Uncertainty*, 2009, *38* (2).

Kahneman, Daniel and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 1979, *47* (2), 263–291.

Keren, Gideon and Martijn C. Willemsen, "Decision Anomalies, Experimenter Assumptions and Participants' Comprehension: Revaluating the Uncertainty Effect," *Journal of Behavioral Decision Making*, 2008, *22* (3), 301–317.

Kreps, David M. and Evan L. Porteus, "Temporal Resolution of Uncertainty and Dynamic Choice Theory," *Econometrica*, 1978, *46* (1), 185–200.

Loomes, Graham and Robert Sugden, "Disappointment and Dynamic Consistency in Choice under Uncertainty," *Review of Economic Studies*, 1986, *53* (2), 271–82.

Magat, Wesley A., W. Kip Viscusi, and Joel Huber, "A Reference Lottery Metric for Valuing Health," *Management Science*, 1996, *42* (8), 1118–1130.

Malinvaud, Edmond, "Note on von Neumann-Morgenstern's Strong Independence," *Econometrica*, 1952, *20* (4), 679.

McCord, Mark and Richard de Neufville, "'Lottery Equivalents': Reduction of the Certainty Effect Problem in Utility Assignment," *Management Science*, 1986, *32* (1), 56–60.

Meier, Stephan and Charles Sprenger, "Present-Biased Preferences and Credit Card Borrowing," *American Economic Journal - Applied Economics*, 2010, *2* (1), 193–210.

Neilson, William S., "Some Mixed Results on Boundary Effects," *Economics Letters*, 1992, *39*, 275–278.

Oliver, Adam, "Testing the Internal Consistency of the Lottery Equivalents Method Using Health Outcomes," *Health Economics*, 2005, *14*, 149–159.

_ , "A Qualitative Analysis of the Lottery Equivalents Method," *Economics and Philosophy*, 2007, *23*, 185–204.

Prelec, Drazen, "The Probability Weighting Function," *Econometrica*, 1998, *66* (3), 497–527.

Quiggin, John, "A Theory of Anticipated Utility," *Journal of Economic Behavior and Organization*, 1982, *3*, 323–343.

Rabin, Matthew, "Risk aversion and expected utility theory: A calibration theorem," *Econometrica*, 2000a, *68* (5), 1281–1292.

_ , "Diminishing Marginal Utility of Wealth Cannot Explain Risk Aversion," in Daniel Kahneman and Amos Tversky, eds., *Choices, Values, and Frames*, New York: Cambridge University Press, 2000b, pp. 202–208.

Rydval, Ondrej, Andreas Ortmann, Sasha Prokosheva, and Ralph Hertwig, "How Certain is the Uncertainty Effect," *Experimental Economics*, 2009, *12*, 473–487.

Samuelson, Paul A., "Probability, Utility, and the Independence Axiom," *Econometrica*, 1952, *20* (4), 670–678.

_ , "Utilité, Préfèrence et Probabilité," in "Colloques Internationaux du Centre Natlonal de la Recherche Scientifique (Econometrie) 40" 1953, pp. 141–150.

Savage, Leonard J., "Une Axiomatisation de Comportement Raisonnable Face à l'Incertitude," in "Colloques Internationaux du Centre Natlonal de la Recherche Scientifique (Econometrie) 40" 1953, pp. 29–33.

_ , *The Foundations of Statistics*, New York: J. Wiley, 1954.

Schmidt, Ulrich, "A Measurement of the Certainty Effect," *Journal of Mathematical Psychology*, 1998, *42* (1), 32–47.

Simonsohn, Uri, "Direct Risk Aversion: Evidence from Risky Prospects Valued Below Their Worst Outcome," *Psychological Science*, 2009, *20* (6), 686–692.

Sonsino, Doron, "Disappointment Aversion in Internet Bidding Decisions," *Theory and Decision*, 2008, *64* (2-3), 363–393.

Starmer, Chris, "Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice Under Risk," *Journal of Economic Literature*, 2000, *38* (2).

_ **and Robert Sugden**, "Does the Random-Lottery Incentive System Elicit True Preferences? An Experimental Investigation," *The American Economic Review*, 1991, *81* (4), 971–978.

Stewart, Mark B., "On Least Squares Estimation when the Dependent Variable is Grouped," *The Review of Economic Studies*, 1983, *50* (4), 737–753.

Tanaka, Tomomi, Colin Camerer, and Quang Nguyen, "Risk and time preferences: Experimental and household data from Vietnam," *American Economic Review*, 2010, *100* (1), 557–571.

Tversky, Amos and Craig R. Fox, "Weighing Risk and Uncertainty," *Psychological Review*, 1995, *102* (2), 269–283.

_ **and Daniel Kahneman**, "Advances in Prospect Theory: Cumulative Representation of Uncertainty," *Journal of Risk and Uncertainty*, 1992, *5* (4), 297–323.

Varian, Hal R., *Microeconomic Analysis*, 3rd ed., New York: Norton, 1992.

von Neumann, John and Oskar Morgenstern, *Theory of Games and Economic Behavior*, Princeton University Press, 1944.

Wakker, Peter P. and Daniel Deneffe, "Eliciting von Neumann-Morgenstern Utilities When Probabilities are Distorted or Unknown," *Management Science*, 1996, *42* (8), 1131–1150.

Wu, George and Richard Gonzalez, "Curvature of the Probability Weighting Function," *Management Science*, 1996, *42* (12), 1676–1690.

A Appendix: NOT FOR PUBLICATION

A.1 Non-Parametric Convexity/Concavity Measures

We investigate the relationship between given p-gambles, $(p; X, Y)$, and their uncertainty equivalents $(q; Y, 0)$ both by analyzing the coefficient of the square term in regressions of q on p and p^2, and by examining non-parametric statistics constructed from examining the convexity or concavity of each combination of ordered triples $\{(p_1, q_1), (p_2, q_2), (p_3, q_3)\} \mid p_1 < p_2 < p_3$. The triples statistic, T_n, is constructed following closely the work of Abrevaya and Jiang (2005), which provides more general discussion and multivariate test statistics. The implemented triples statistic specifically is discussed in a prior working paper (Abrevaya and Jiang, 2003).

Each decision theory makes a prediction for the relationship between p and q, such that the model under consideration is

$$q_i = f(p_i) + \epsilon_i, \; E[\epsilon_i | x_i] = 0, \; (i = 1, ..., n),$$

where ϵ_i is an iid, conditionally exogenous disturbance term. The objective is to analyze whether the function $f(\cdot)$ is concave, convex, or linear on the unit interval.

<u>Definition:</u> A function $f : [0, 1] \to R$ is convex (concave) if $a_1 f(p_1) + a_2 f(p_2) + a_3 f(p_3) \geq f(a_1 p_1 + a_2 p_2 + a_3 p_3)$ for any collection of $p_1, p_2, p_3 \in [0, 1]$ and non-negative weights a_1, a_2, a_3 such that $a_1 + a_2 + a_3 = 1$.

Relatedly, if $f(\cdot)$ is a convex function, then

$$p_1 < p_2 < p_3 \in [0, 1] \Rightarrow \frac{f(p_2) - f(p_1)}{p_2 - p_1} \leq \frac{f(p_3) - f(p_2)}{p_3 - p_2}.$$ [37]

This provides a useful basis for testing the relationship between p and q. Following the construction of Abrevaya and Jiang (2003, 2005), note that

$$\frac{q_2 - q_1}{p_2 - p_1} < \frac{q_3 - q_2}{p_3 - p_2} \Leftrightarrow \frac{f(p_2) + \epsilon_2 - f(p_1) - \epsilon_1}{p_2 - p_1} < \frac{f(p_3) + \epsilon_3 - f(p_2) - \epsilon_2}{p_3 - p_2}$$
$$\frac{f(p_2) - f(p_1)}{p_2 - p_1} - \frac{f(p_3) - f(p_2)}{p_3 - p_2} < \frac{\epsilon_3 - \epsilon_2}{p_3 - p_2} - \frac{\epsilon_2 - \epsilon_1}{p_2 - p_1}$$

Given that the ϵ are zero in expectation and are iid, the right hand side of the last equation is zero on average. Under these assumptions the concavity or convexity of the function $f(\cdot)$ is reflected in the data triple $\{(p_1, q_1), (p_2, q_2), (p_3, q_3)\} \mid p_1 < p_2 < p_3$

[37] To see this consider a convex function satisfying $a_1 f(p_1) + (1 - a_1 - a_3) f(p_2) + a_3 f(p_3) \geq f(a_1 p_1 + (1 - a_1 - a_3) p_2 + a_3 p_3)$ for all $a_1, a_3 \in [0, 1]$. Consider the case where $a_1 p_1 + (1 - a_1 - a_3) p_2 + a_3 p_3 = p_2$ such that $a_1(p_1 - p_2) + a_3(p_3 - p_2) = 0$. Then $a_1 f(p_1) + (1 - a_1 - a_3) f(p_2) + a_3 f(p_3) \geq f(p_2)$. Correspondingly, $a_1(f(p_1) - f(p_2)) + a_3(f(p_3) - f(p_2)) \geq 0$, or $a_1(f(p_2) - f(p_1)) \leq a_3(f(p_3) - f(p_2))$. Note that if $p_1 < p_2 < p_3$, then the number $a_3(p_3 - p_2) = a_1(p_2 - p_1)$ is positive. Divide by $a_3(p_3 - p_2) = a_1(p_2 - p_1)$ and we have $\frac{f(p_2) - f(p_1)}{p_2 - p_1} \leq \frac{f(p_3) - f(p_2)}{p_3 - p_2}$.

We define the slope between two order points $\{(p_i, q_i), (p_j, q_j)|p_i < p_j\}$ as

$$m_{ij} \equiv \frac{q_i - q_j}{p_i - p_j},$$

and define the triples statistic, T_n as

$$\binom{n}{3}^{-1} \sum_{i<j<k} sign(m_{jk} - m_{ij})$$

where the summation is shorthand for summing over all combinations of ordered triples in the data. The functions $sign(\cdot)$ captures the convexity or concavity of an ordered triple, $sign(x) = 1$ if $x > 0$, -1 if $x < 0$, and 0 if $x = 0$. Following the logic above, a triple is convex if $sign(m_{jk} - m_{ij}) > 0$, a triple is concave if $sign(m_{jk} - m_{ij}) < 0$, and a triple is linear if $sign(m_{jk} - m_{ij}) = 0$.

The statistic T_n takes all combinations of potential triples in a set of data with n observations and counts the number of convex and concave triples. As T_n simply represents the percentage of convex triples minus the percentage of concave triples in a given data set, it also acts as a convenient description of the data and is a measure along which we describe behavior.

Abrevaya and Jiang (2003, 2005) prove that under the assumptions of an iid sample drawn from the considered model

$$\sqrt{n}(T_n - \theta_T) \to N(0, 9\zeta_T)$$

where $\theta_T \equiv E[sign(m_{jk} - m_{ij})|x_i < x_j < x_k]$ and $9\zeta_T$ is the asymptotic variance, with the 9 inherited from the nature of the statistic as a 3rd order U-statistic. A consistent estimator of ζ_T is provided by

$$\hat{\zeta}_T \equiv n^{-1} \sum_{i=1}^{n} (\binom{n-1}{2}^{-1} \sum_{j<k, j\neq i, k\neq i} h_T(v_i, v_j, v_k) - T_n)^2,$$

with $h_T(v_i, v_j, v_k)$ given by

$$h_T(v_i, v_j, v_k) \equiv \sum_{i,j,k} 1(x_i < x_j < x_k) \cdot sign(m_{jk} - m_{ij})$$

The null hypothesis of linearity $\theta_T = 0$ is easily tested by examining the value of

$$z = \frac{\sqrt{n} T_n}{3\sqrt{\hat{\zeta}_T}},$$

distributed standard normal under the null.

For our simulations, we modify slightly the calculation of T_n, to account for the interval nature of the data. We conservatively consider a triple, $\{(p_1, q_1), (p_2, q_2), (p_3, q_3)\} \mid p_1 < p_2 < p_3$, to be convex if the triple remains convex when evaluated at the low ends of the intervals for q_1 and q_3. Likewise, a triple is considered concave if the triple remains concave when evaluated at the low end of the interval for q_2.

In order to gain some initial intuition as to the values of these non-parametric test statistics, we create data following the behavioral decision theories considered in this paper for our experimental context. To be specific, we consider both cumulative and non-cumulative prospect theory probability weighting with S-shaped weighting and curvature parameter $\gamma = 0.61$, disappointment aversion with loss aversion parameter $\lambda = 2.5$, and u-v preferences with risk neutrality under uncertainty, $u(x) = x^1$, and a specific preference for certainty, $v(x) = x^{1.1}$. Sample individuals are placed in our experimental context, their decisions predicted, and corresponding regression and non-parametric test statistics calculated.

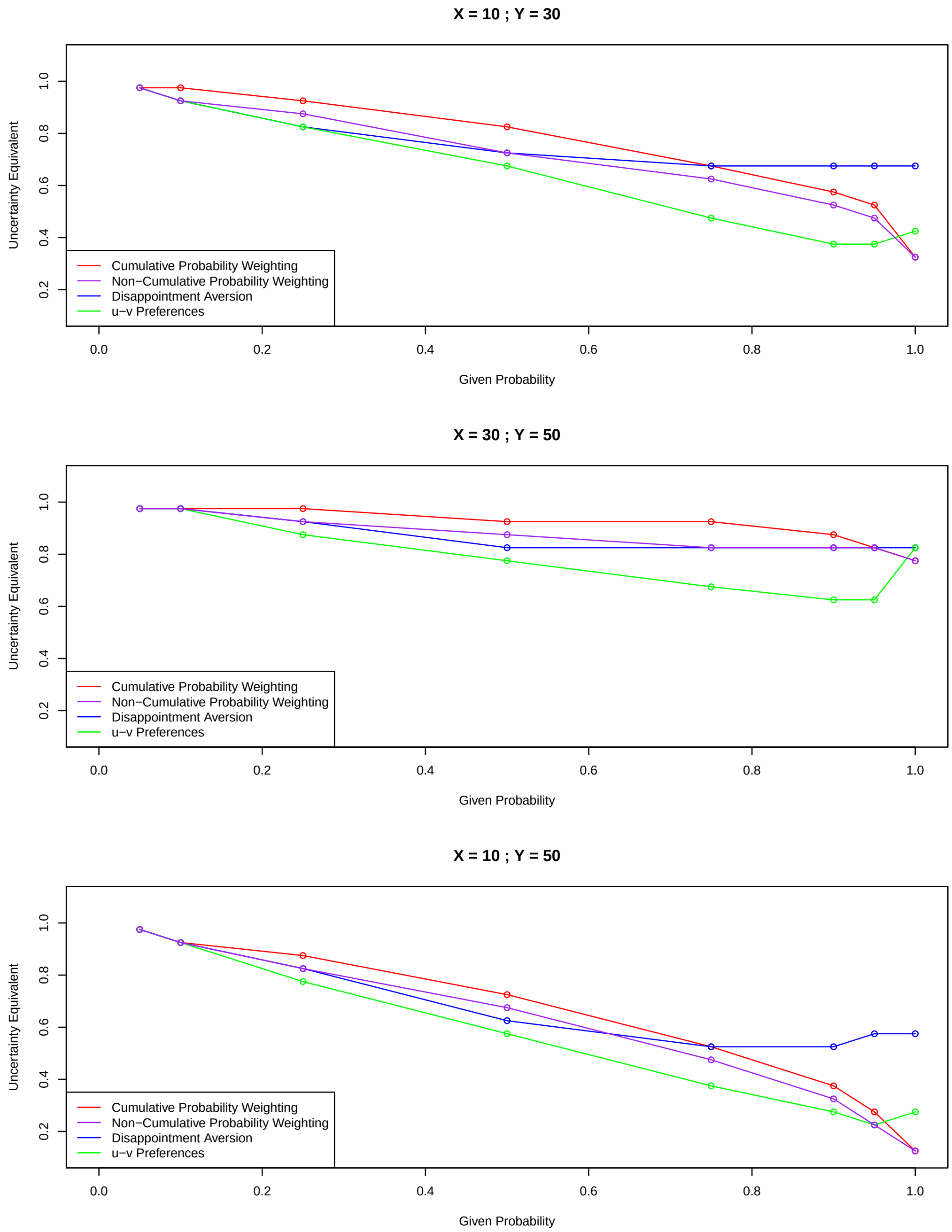
We provide a graphical presentation of the sample data for the considered behavioral decision theories in Figure A1. Additionally, Table A1 provides the corresponding regression and non-parametric statistics and p-values for the sample data both using standard regression of the midpoint of q on p and p^2 and the non-parametric strategy outlined above.

First, for CPT probability weighting with the standard functional form of $\pi(p) = p^\gamma/(p^\gamma + (1-p)^\gamma)^{(1/\gamma)}$, a linear utility function and $\gamma = 0.61$. A sample individual with such preferences would behave as in the solid red line in Figure A1. Note that a substantially concave relationship is obtained. Taking each interval midpoint for q and regressing on p and p^2 a negative square term is obtained for all three payment sets. Likewise, non-parametric test statistics show that the percentage of concave triples exceeds the percentage of convex triples by between 21 to 63% in each payment set. Further, even with a limited number of observations in each payment set, we reject the null hypothesis of linearity. For a CPT decision-maker with standard functional forms and parameter values, the uncertainty equivalent environment is sufficient for both eliciting and precisely identifying the concave shape to the data.

Second, we consider non-cumulative prospect theory probability weighting as originally proposed in Kahneman and Tversky (1979). We consider $\pi(p) = p^\gamma/(p^\gamma + (1-p)^\gamma)^(1/\gamma)$, but allow each outcome to be weighted individually such that $\pi(p) + \pi(1-p) \neq 1$, generally. We again consider a linear utility function and $\gamma = 0.61$. A sample individual with such preferences would behave as the solid purple line in Figure A1. Important to note, we again document substantially concave relationships between p and q in two of our three payment sets. However, the uncertainty equivalent environment is not precise enough to identify the shape of the weighting function in the payment set $(X, Y) = (30, 50)$. In this condition, all triples are plausibly linear, and no inference can be made. However, the broad patterns of a concave relationship are maintained both in the non-parametric tests and regression coefficients.

Third, we investigate disappointment aversion as described in Section 5. Disappointment aversion is equivalent to cumulative prospect theory with a global shape to the weighting function. We consider $\lambda = 2.5, \eta = 1$ such that the behavior is equivalent to underweighting all probabilities. Further, as we consider $\lambda > 2, \eta = 1$, the model will generate violations of first order stochastic dominance close to $p = 1$ in some contexts. A sample individual with such preferences would behave as the solid blue line

Figure A1: Simulated Data



Note: Midpoints of interval responses for simulated data following four behavioral decisions theories: 1) Cumulative Prospect Theory with S-shaped probability weighting (red); 2) Non-Cumulative Probability Weighting (purple); 3) Disappointment Aversion (blue); 4) u-v Preferences (green).

in Figure A1. In both the regression and non-parametric tests we document convexity to the relationship. Positive square terms are obtained in each regression context. The

Table A1: Simulation Statistics

	(1) $(X,Y) = (\$10,\$30)$	(2) $(X,Y) = (\$30,\$50)$	(3) $(X,Y) = (\$10,\$50)$
Panel A: Cumulative Prospect Theory, $\pi(p) = p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{(1/\gamma)}$, $\gamma = 0.61$			
Non-Parametric Statistics			
T_n	-0.4107	-0.2143	-0.6250
9*$\hat{\zeta}_T$	0.0100	0.0164	0.0381
z	-11.6438	-4.7329	-9.0558
	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.01)$
Regression Estimates			
Constant	0.9629	0.9633	0.9522
β_p	0.0898	0.1274	-0.0605
β_{p^2}	-0.6409	-0.2860	-0.7069
Panel B: Non-Cumulative Prospect Theory, $\pi(p) = p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{(1/\gamma)}$, $\gamma = 0.61$			
Non-Parametric Statistics			
T_n	-0.3036	0.0000	-0.4643
9*$\hat{\zeta}_T$	0.0217	0.0000	0.0382
z	-5.8279	-	-6.7212
	$(p < 0.01)$	$(-)$	$(p < 0.01)$
Regression Estimates			
Constant	0.9649	0.9925	0.9680
β_p	-0.2476	-0.2702	-0.3293
β_{p^2}	-0.3208	0.0767	-0.4755
Panel C: Disappointment Aversion $\lambda = 2.5, \eta = 1$			
Non-Parametric Statistics			
T_n	0.3393	0.1964	0.5714
9*$\hat{\zeta}_T$	0.1028	0.0101	0.0255
z	2.9932	5.5185	10.1193
	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.01)$
Regression Estimates			
Constant	1.0055	1.0116	1.0467
β_p	-0.8070	-0.4856	-1.2089
β_{p^2}	0.4828	0.3035	0.7268
Panel D: u-v Preferences: $u(x) = x^1, v(x) = x^{1.1}$			
Non-Parametric Statistics			
T_n	0.2500	0.3571	0.2679
9*$\hat{\zeta}_T$	0.0249	0.0219	0.0019
z	4.4836	6.8313	17.2183
	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.01)$
Regression Estimates			
Constant	1.0192	1.0476	1.0315
β_p	-0.8572	-0.8968	-1.0923
β_{p^2}	0.2093	0.5570	0.2955

Notes: Non-parametric T_n statistics and z scores for the null hypothesis $H_0 : \theta = 0$ against a two-sided alternative. Regression coefficients from the regression of the midpoint of the uncertainty equivalent q on a constant p and p^2.

non-parametric test statistics show that the percentage of convex triples exceeds the percentage of concave triples by between 20 to 60% in each payment set. Further, we reject the null hypothesis of linearity even with a limited number of observations in each set. Hence, the uncertainty equivalent environment is sufficient for both eliciting and precisely identifying the convex shape to the data predicted under disappointment aversion.

Fourth, we consider u-v preferences with the following parametric specification. Under uncertainty, individuals act according to the risk neutral utility function $u(x) = x^1$ while under certainty they act according to $v(x) = x^{1.1}$. A sample individual with such preferences would behave as the solid green line in Figure A1. Similar to disappointment averse preferences, a substantially convex relationship is obtained both in regression and in the non-parametric tests.

The conducted exercise is meant to serve as a proving ground for the uncertainty equivalent technique and our methods of analysis. If individuals behave according to specific behavioral decision theories, the corresponding predicted concave, convex, or linear relationships can both be uncovered and identified both in regression and via non-parametric test statistics.

A.2 Experimental Instructions

Hello and Welcome.

ELIGIBILITY FOR THIS STUDY: To be in this study, you must be a UCSD student. There are no other requirements. The study will be completely anonymous. We will not collect your name, student PID or any other identifying information. You have been assigned a participant number and it is on the note card in front of you. This number will be used throughout the study. Please inform us if you do not know or cannot read your participant number.

EARNING MONEY:

To begin, you will be given a \$5 minimum payment. This \$5 is yours. Whatever you earn from the study today will be added to this minimum payment. All payments will be made in cash at the end of the study today.

In this study you will make choices between two options. The first option will always be called OPTION A. The second option will always be called OPTION B. In each decision, all you have to do is decide whether you prefer OPTION A or OPTION B. These decisions will be made in 5 separate blocks of tasks. Each block of tasks is slightly different, and so new instructions will be read at the beginning of each task block.

Once all of the decision tasks have been completed, we will randomly select one decision as the decision-that-counts. If you preferred OPTION A, then OPTION A would be implemented. If you preferred OPTION B, then OPTION B would be implemented.

Throughout the tasks, either OPTION A, OPTION B or both will involve chance. You will be fully informed of the chance involved for every decision. Once we know which is the decision-that-counts, and whether you prefer OPTION A or OPTION B, we will then determine the value of your payments.

For example, OPTION A could be a 75 in 100 chance of receiving \$10 and a 25 in 100 chance of receiving \$30. This might be compared to OPTION B of a 50 in 100 chance of receiving \$30 and a 50 in 100 chance of receiving nothing. Imagine for a moment which one you would prefer. You have been provided with a calculator to help you in your decisions.

If this was chosen as the decision-that-counts, and you preferred OPTION A, we would then randomly choose a number from 1 to 100. This will be done by throwing two ten-sided die: one for the tens digit and one for the ones digit (0-0 will be 100). If the chosen number was between 1 and 75 (inclusive) you would receive \$10 (+5 minimum payment) = \$15. If the number was between 76 and 100 (inclusive) you would receive \$30 (+5 minimum payment) = \$35. If, instead, you preferred OPTION B, we would again randomly choose a number from 1 to 100. If the chosen number was between 1 and 50 (inclusive) you'd receive \$0 (+5 minimum payment) = \$5. If the number was between 51 and 100 (inclusive) you'd receive \$30 (+5 minimum payment) = \$35.

In a moment we will begin the first task.

A.3 Sample Uncertainty Equivalents

TASKS 1-8

On the following pages you will complete 8 tasks. In each task you are asked to make a series of decisions between two uncertain options: Option A and Option B.

In each task, Option A will be fixed, while Option B will vary. For example, in Task 1 Option A will be a 5 in 100 chance of $10 and a 95 in 100 chance of $30. This will remain the same for all decisions in the task. Option B will vary across decisions. Initially Option B will be a 5 in 100 chance of $30 and a 95 in 100 chance of nothing. As you proceed, Option B will change. The chance of receiving $30 will increase, while the chance of receiving nothing will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by checking the corresponding box. Most people begin by preferring Option A and then switch to Option B, so one way to view this task is to determine the best row to switch from Option A to Option B.

The first question from Task 1 is reproduced as an example.

EXAMPLE

	Option A			*or*	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
1)	5 in 100	95 in 100	☐	*or*	95 in 100	5 in 100	☐
If your prefer Option A, check the green box...							
1)	5 in 100	95 in 100	☑	*or*	95 in 100	5 in 100	☐
If your prefer Option B, check the blue box...							
1)	5 in 100	95 in 100	☐	*or*	95 in 100	5 in 100	☑

Remember, each decision could be the **decision-that-counts**. So, it is in your interest to treat each decision as if it could be the one that determines your payments.

TASK 1

On this page you will make a series of decisions between two uncertain options. Option A will be a 5 in 100 chance of $10 and a 95 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 95 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			or	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
	5 in 100	95 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	5 in 100	95 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	5 in 100	95 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	5 in 100	95 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	5 in 100	95 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	5 in 100	95 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	5 in 100	95 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	5 in 100	95 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	5 in 100	95 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	5 in 100	95 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	5 in 100	95 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	5 in 100	95 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	5 in 100	95 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	5 in 100	95 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	5 in 100	95 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	5 in 100	95 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	5 in 100	95 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	5 in 100	95 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	5 in 100	95 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	5 in 100	95 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	5 in 100	95 in 100	☐	*or*	1 in 100	99 in 100	☐
	5 in 100	95 in 100	☐	*or*	0 in 100	100 in 100	☑

TASK 2

On this page you will make a series of decisions between two uncertain options. Option A will be a 10 in 100 chance of $10 and a 90 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 95 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			*or*	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
	10 in 100	90 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	10 in 100	90 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	10 in 100	90 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	10 in 100	90 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	10 in 100	90 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	10 in 100	90 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	10 in 100	90 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	10 in 100	90 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	10 in 100	90 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	10 in 100	90 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	10 in 100	90 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	10 in 100	90 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	10 in 100	90 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	10 in 100	90 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	10 in 100	90 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	10 in 100	90 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	10 in 100	90 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	10 in 100	90 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	10 in 100	90 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	10 in 100	90 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	10 in 100	90 in 100	☐	*or*	1 in 100	99 in 100	☐
	10 in 100	90 in 100	☐	*or*	0 in 100	100 in 100	☑

TASK 3

On this page you will make a series of decisions between two uncertain options. Option A will be a 25 in 100 chance of $10 and a 75 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 95 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			*or*	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
	25 in 100	75 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	25 in 100	75 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	25 in 100	75 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	25 in 100	75 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	25 in 100	75 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	25 in 100	75 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	25 in 100	75 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	25 in 100	75 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	25 in 100	75 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	25 in 100	75 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	25 in 100	75 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	25 in 100	75 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	25 in 100	75 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	25 in 100	75 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	25 in 100	75 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	25 in 100	75 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	25 in 100	75 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	25 in 100	75 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	25 in 100	75 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	25 in 100	75 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	25 in 100	75 in 100	☐	*or*	1 in 100	99 in 100	☐
	25 in 100	75 in 100	☐	*or*	0 in 100	100 in 100	☑

TASK 4

On this page you will make a series of decisions between two uncertain options. Option A will be a 50 in 100 chance of $10 and a 50 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 95 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A: Chance of $10	Option A: Chance of $30		or	Option B: Chance of $0	Option B: Chance of $30	
	50 in 100	50 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	50 in 100	50 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	50 in 100	50 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	50 in 100	50 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	50 in 100	50 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	50 in 100	50 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	50 in 100	50 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	50 in 100	50 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	50 in 100	50 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	50 in 100	50 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	50 in 100	50 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	50 in 100	50 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	50 in 100	50 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	50 in 100	50 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	50 in 100	50 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	50 in 100	50 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	50 in 100	50 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	50 in 100	50 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	50 in 100	50 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	50 in 100	50 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	50 in 100	50 in 100	☐	*or*	1 in 100	99 in 100	☐
	50 in 100	50 in 100	☐	*or*	0 in 100	100 in 100	☑

TASK 5

On this page you will make a series of decisions between two uncertain options. Option A will be a 75 in 100 chance of $10 and a 25 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 95 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			or	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
	75 in 100	25 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	75 in 100	25 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	75 in 100	25 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	75 in 100	25 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	75 in 100	25 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	75 in 100	25 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	75 in 100	25 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	75 in 100	25 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	75 in 100	25 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	75 in 100	25 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	75 in 100	25 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	75 in 100	25 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	75 in 100	25 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	75 in 100	25 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	75 in 100	25 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	75 in 100	25 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	75 in 100	25 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	75 in 100	25 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	75 in 100	25 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	75 in 100	25 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	75 in 100	25 in 100	☐	*or*	1 in 100	99 in 100	☐
	75 in 100	25 in 100	☐	*or*	0 in 100	100 in 100	☑

TASK 6

On this page you will make a series of decisions between two uncertain options. Option A will be a 90 in 100 chance of $10 and a 10 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 95 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			*or*	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
	90 in 100	10 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	90 in 100	10 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	90 in 100	10 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	90 in 100	10 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	90 in 100	10 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	90 in 100	10 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	90 in 100	10 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	90 in 100	10 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	90 in 100	10 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	90 in 100	10 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	90 in 100	10 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	90 in 100	10 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	90 in 100	10 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	90 in 100	10 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	90 in 100	10 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	90 in 100	10 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	90 in 100	10 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	90 in 100	10 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	90 in 100	10 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	90 in 100	10 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	90 in 100	10 in 100	☐	*or*	1 in 100	99 in 100	☐
	90 in 100	10 in 100	☐	*or*	0 in 100	100 in 100	☑

TASK 7

On this page you will make a series of decisions between two uncertain options. Option A will be a 95 in 100 chance of $10 and a 5 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 95 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			or	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
	95 in 100	5 in 100	☑	*or*	100 in 100	0 in 100	☐
1)	95 in 100	5 in 100	☐	*or*	95 in 100	5 in 100	☐
2)	95 in 100	5 in 100	☐	*or*	90 in 100	10 in 100	☐
3)	95 in 100	5 in 100	☐	*or*	85 in 100	15 in 100	☐
4)	95 in 100	5 in 100	☐	*or*	80 in 100	20 in 100	☐
5)	95 in 100	5 in 100	☐	*or*	75 in 100	25 in 100	☐
6)	95 in 100	5 in 100	☐	*or*	70 in 100	30 in 100	☐
7)	95 in 100	5 in 100	☐	*or*	65 in 100	35 in 100	☐
8)	95 in 100	5 in 100	☐	*or*	60 in 100	40 in 100	☐
9)	95 in 100	5 in 100	☐	*or*	55 in 100	45 in 100	☐
10)	95 in 100	5 in 100	☐	*or*	50 in 100	50 in 100	☐
11)	95 in 100	5 in 100	☐	*or*	45 in 100	55 in 100	☐
12)	95 in 100	5 in 100	☐	*or*	40 in 100	60 in 100	☐
13)	95 in 100	5 in 100	☐	*or*	35 in 100	65 in 100	☐
14)	95 in 100	5 in 100	☐	*or*	30 in 100	70 in 100	☐
15)	95 in 100	5 in 100	☐	*or*	25 in 100	75 in 100	☐
16)	95 in 100	5 in 100	☐	*or*	20 in 100	80 in 100	☐
17)	95 in 100	5 in 100	☐	*or*	15 in 100	85 in 100	☐
18)	95 in 100	5 in 100	☐	*or*	10 in 100	90 in 100	☐
19)	95 in 100	5 in 100	☐	*or*	5 in 100	95 in 100	☐
20)	95 in 100	5 in 100	☐	*or*	1 in 100	99 in 100	☐
	95 in 100	5 in 100	☐	*or*	0 in 100	100 in 100	☑

TASK 8

On this page you will make a series of decisions between two uncertain options. Option A will be a 100 in 100 chance of $10 and a 5 in 100 chance of $30. Option B will vary across decisions. Initially, Option B will be a 100 in 100 chance of $0 and a 5 in 100 chance of $30. As you proceed down the rows, Option B will change. The chance of receiving $30 will increase, while the chance of receiving $0 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			or	Option B		
	Chance of $10	Chance of $30			Chance of $0	Chance of $30	
	100 in 100	0 in 100	☑	or	100 in 100	0 in 100	☐
1)	100 in 100	0 in 100	☐	or	95 in 100	5 in 100	☐
2)	100 in 100	0 in 100	☐	or	90 in 100	10 in 100	☐
3)	100 in 100	0 in 100	☐	or	85 in 100	15 in 100	☐
4)	100 in 100	0 in 100	☐	or	80 in 100	20 in 100	☐
5)	100 in 100	0 in 100	☐	or	75 in 100	25 in 100	☐
6)	100 in 100	0 in 100	☐	or	70 in 100	30 in 100	☐
7)	100 in 100	0 in 100	☐	or	65 in 100	35 in 100	☐
8)	100 in 100	0 in 100	☐	or	60 in 100	40 in 100	☐
9)	100 in 100	0 in 100	☐	or	55 in 100	45 in 100	☐
10)	100 in 100	0 in 100	☐	or	50 in 100	50 in 100	☐
11)	100 in 100	0 in 100	☐	or	45 in 100	55 in 100	☐
12)	100 in 100	0 in 100	☐	or	40 in 100	60 in 100	☐
13)	100 in 100	0 in 100	☐	or	35 in 100	65 in 100	☐
14)	100 in 100	0 in 100	☐	or	30 in 100	70 in 100	☐
15)	100 in 100	0 in 100	☐	or	25 in 100	75 in 100	☐
16)	100 in 100	0 in 100	☐	or	20 in 100	80 in 100	☐
17)	100 in 100	0 in 100	☐	or	15 in 100	85 in 100	☐
18)	100 in 100	0 in 100	☐	or	10 in 100	90 in 100	☐
19)	100 in 100	0 in 100	☐	or	5 in 100	95 in 100	☐
20)	100 in 100	0 in 100	☐	or	1 in 100	99 in 100	☐
	100 in 100	0 in 100	☐	or	0 in 100	100 in 100	☑

A.4 Sample Holt-Laury Tasks

TASKS 25-26

On the following pages you will complete 2 tasks. In each task you are asked to make a series of decisions between two uncertain options: Option A and Option B.

In each task, both Option A and Option B will vary. For example, in Task 25, question 1 Option A will be a 10 in 100 chance of $5.20 and a 90 in 100 chance of $4.15. Option B will be a 10 in 100 chance of $10 and a 90 in 100 chance of $0.26.

As you proceed, both Option A and Option B will change. For Option A, the chance of receiving $5.20 will increase and the chance of receiving $4.15 will decrease. For Option B, the chance of receiving $10 will increase, while the chance of receiving $0.26 will decrease. For each row, all you have to do is decide whether you prefer Option A or Option B. Most people begin by preferring Option A and then switch to Option B, so one way to view this task is to determine the best row to switch from Option A to Option B.

The first question from Task 25 is reproduced as an example.

EXAMPLE

	Option A			*or*	Option B		
	Chance of $5.20	Chance of $4.15			Chance of $10	Chance of $0.26	
1)	10 in 100	90 in 100	☐	*or*	10 in 100	90 in 100	☐
If your prefer Option A, check the green box...							
1)	10 in 100	90 in 100	☑	*or*	10 in 100	90 in 100	☐
If your prefer Option B, check the blue box...							
1)	10 in 100	90 in 100	☐	*or*	10 in 100	90 in 100	☑

Remember, each decision could be the **decision-that-counts**. So, treat each decision as if it could be the one that determines your payments.

TASK 25

On this page you will make a series of decisions between two uncertain options. Option A involves payments of \$5.20 and \$4.15. Option B involves payments of \$10 and \$0.26. As you proceed, both Option A and Option B will change. For Option A, the chance of receiving \$5.20 will increase and the chance of receiving \$4.15 will decrease. For Option B, the chance of receiving \$10 will increase, while the chance of receiving \$0.26 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference, by checking the corresponding box.

	Option A			or	Option B		
	Chance of \$5.20	Chance of \$4.15			Chance of \$10	Chance of \$0.26	
	0 in 100	100 in 100	☑	*or*	0 in 100	100 in 100	☐
1)	10 in 100	90 in 100	☐	*or*	10 in 100	90 in 100	☐
2)	20 in 100	80 in 100	☐	*or*	20 in 100	80 in 100	☐
3)	30 in 100	70 in 100	☐	*or*	30 in 100	70 in 100	☐
4)	40 in 100	60 in 100	☐	*or*	40 in 100	60 in 100	☐
5)	50 in 100	50 in 100	☐	*or*	50 in 100	50 in 100	☐
6)	60 in 100	40 in 100	☐	*or*	60 in 100	40 in 100	☐
7)	70 in 100	30 in 100	☐	*or*	70 in 100	30 in 100	☐
8)	80 in 100	20 in 100	☐	*or*	80 in 100	20 in 100	☐
9)	90 in 100	10 in 100	☐	*or*	90 in 100	10 in 100	☐
	100 in 100	0 in 100	☐	*or*	100 in 100	0 in 100	☑

TASK 26

On this page you will make a series of decisions between two uncertain options. Option A involves payments of \$15.59 and \$12.47. Option B involves payments of \$30 and \$0.78. As you proceed, both Option A and Option B will change. For Option A, the chance of receiving \$15.59 will increase and the chance of receiving \$12.47 will decrease. For Option B, the chance of receiving \$30 will increase, while the chance of receiving \$0.78 will decrease.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference, by checking the corresponding box.

	Option A: Chance of \$15.59	Option A: Chance of \$12.47		or	Option B: Chance of \$30	Option B: Chance of \$0.78	
	0 in 100	100 in 100	☑	*or*	0 in 100	100 in 100	☐
1)	10 in 100	90 in 100	☐	*or*	10 in 100	90 in 100	☐
2)	20 in 100	80 in 100	☐	*or*	20 in 100	80 in 100	☐
3)	30 in 100	70 in 100	☐	*or*	30 in 100	70 in 100	☐
4)	40 in 100	60 in 100	☐	*or*	40 in 100	60 in 100	☐
5)	50 in 100	50 in 100	☐	*or*	50 in 100	50 in 100	☐
6)	60 in 100	40 in 100	☐	*or*	60 in 100	40 in 100	☐
7)	70 in 100	30 in 100	☐	*or*	70 in 100	30 in 100	☐
8)	80 in 100	20 in 100	☐	*or*	80 in 100	20 in 100	☐
9)	90 in 100	10 in 100	☐	*or*	90 in 100	10 in 100	☐
	100 in 100	0 in 100	☐	*or*	100 in 100	0 in 100	☑

A.5 Sample Certainty Equivalents

TASKS 27-33

On the following pages you will complete 7 tasks. In each task you are asked to make a series of decisions between two options: Option A and Option B.

In each task, Option A will be fixed, while Option B will vary. For example, in Task 27 Option A will be a 5 in 100 chance of $30 and a 95 in 100 chance of $0. This will remain the same for all decisions in the task. Option B will vary across decisions. Initially Option B will be a $0.50 for sure. As you proceed, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by checking the corresponding box. Most people begin by preferring Option A and then switch to Option B, so one way to view this task is to determine the best row to switch from Option A to Option B.

The first question from Task 27 is reproduced as an example.

EXAMPLE

	Option A			*or*	Option B	
	Chance of $30	Chance of $0			Sure Amount	
1)	5 in 100	95 in 100	☐	*or*	$0.50 for sure	☐
If your prefer Option A, check the green box...						
1)	5 in 100	95 in 100	☑	*or*	$0.50 for sure	☐
If your prefer Option B, check the blue box...						
1)	5 in 100	95 in 100	☐	*or*	$0.50 for sure	☑

Remember, each decision could be the **decision-that-counts**. So, it is in your best interest to treat each decision as if it could be the one that determines your payments.

TASK 27

On this page you will make a series of decisions between two options. Option A will be a 5 in 100 chance of $30 and a 95 in 100 chance of $0. Option B will vary across decisions. Initially, Option B will be a $0.50 for sure. As you proceed down the rows, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			or	Option B	
	Chance of $30	Chance of $0			Sure Amount	
	5 in 100	95 in 100	☑	or	$0.00 for sure	☐
1)	5 in 100	95 in 100	☐	or	$0.50 for sure	☐
2)	5 in 100	95 in 100	☐	or	$1.00 for sure	☐
3)	5 in 100	95 in 100	☐	or	$1.50 for sure	☐
4)	5 in 100	95 in 100	☐	or	$2.50 for sure	☐
5)	5 in 100	95 in 100	☐	or	$3.50 for sure	☐
6)	5 in 100	95 in 100	☐	or	$4.50 for sure	☐
7)	5 in 100	95 in 100	☐	or	$6.50 for sure	☐
8)	5 in 100	95 in 100	☐	or	$8.50 for sure	☐
9)	5 in 100	95 in 100	☐	or	$10.50 for sure	☐
10)	5 in 100	95 in 100	☐	or	$13.50 for sure	☐
11)	5 in 100	95 in 100	☐	or	$16.50 for sure	☐
12)	5 in 100	95 in 100	☐	or	$19.50 for sure	☐
13)	5 in 100	95 in 100	☐	or	$21.50 for sure	☐
14)	5 in 100	95 in 100	☐	or	$23.50 for sure	☐
15)	5 in 100	95 in 100	☐	or	$25.50 for sure	☐
16)	5 in 100	95 in 100	☐	or	$26.50 for sure	☐
17)	5 in 100	95 in 100	☐	or	$27.50 for sure	☐
18)	5 in 100	95 in 100	☐	or	$28.50 for sure	☐
19)	5 in 100	95 in 100	☐	or	$29.00 for sure	☐
20)	5 in 100	95 in 100	☐	or	$29.50 for sure	☐
	5 in 100	95 in 100	☐	or	$30.00 for sure	☑

TASK 28

On this page you will make a series of decisions between two options. Option A will be a 10 in 100 chance of $30 and a 90 in 100 chance of $0. Option B will vary across decisions. Initially, Option B will be a $0.50 for sure. As you proceed down the rows, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A				Option B	
	Chance of $30	Chance of $0		*or*	Sure Amount	
	10 in 100	90 in 100	☑	*or*	$0.00 for sure	☐
1)	10 in 100	90 in 100	☐	*or*	$0.50 for sure	☐
2)	10 in 100	90 in 100	☐	*or*	$1.00 for sure	☐
3)	10 in 100	90 in 100	☐	*or*	$1.50 for sure	☐
4)	10 in 100	90 in 100	☐	*or*	$2.50 for sure	☐
5)	10 in 100	90 in 100	☐	*or*	$3.50 for sure	☐
6)	10 in 100	90 in 100	☐	*or*	$4.50 for sure	☐
7)	10 in 100	90 in 100	☐	*or*	$6.50 for sure	☐
8)	10 in 100	90 in 100	☐	*or*	$8.50 for sure	☐
9)	10 in 100	90 in 100	☐	*or*	$10.50 for sure	☐
10)	10 in 100	90 in 100	☐	*or*	$13.50 for sure	☐
11)	10 in 100	90 in 100	☐	*or*	$16.50 for sure	☐
12)	10 in 100	90 in 100	☐	*or*	$19.50 for sure	☐
13)	10 in 100	90 in 100	☐	*or*	$21.50 for sure	☐
14)	10 in 100	90 in 100	☐	*or*	$23.50 for sure	☐
15)	10 in 100	90 in 100	☐	*or*	$25.50 for sure	☐
16)	10 in 100	90 in 100	☐	*or*	$26.50 for sure	☐
17)	10 in 100	90 in 100	☐	*or*	$27.50 for sure	☐
18)	10 in 100	90 in 100	☐	*or*	$28.50 for sure	☐
19)	10 in 100	90 in 100	☐	*or*	$29.00 for sure	☐
20)	10 in 100	90 in 100	☐	*or*	$29.50 for sure	☐
	10 in 100	90 in 100	☐	*or*	$30.00 for sure	☑

TASK 29

On this page you will make a series of decisions between two options. Option A will be a 25 in 100 chance of $30 and a 75 in 100 chance of $0. Option B will vary across decisions. Initially, Option B will be a $0.50 for sure. As you proceed down the rows, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			*or*	Option B	
	Chance of $30	Chance of $0			Sure Amount	
	25 in 100	75 in 100	☑	*or*	$0.00 for sure	☐
1)	25 in 100	75 in 100	☐	*or*	$0.50 for sure	☐
2)	25 in 100	75 in 100	☐	*or*	$1.00 for sure	☐
3)	25 in 100	75 in 100	☐	*or*	$1.50 for sure	☐
4)	25 in 100	75 in 100	☐	*or*	$2.50 for sure	☐
5)	25 in 100	75 in 100	☐	*or*	$3.50 for sure	☐
6)	25 in 100	75 in 100	☐	*or*	$4.50 for sure	☐
7)	25 in 100	75 in 100	☐	*or*	$6.50 for sure	☐
8)	25 in 100	75 in 100	☐	*or*	$8.50 for sure	☐
9)	25 in 100	75 in 100	☐	*or*	$10.50 for sure	☐
10)	25 in 100	75 in 100	☐	*or*	$13.50 for sure	☐
11)	25 in 100	75 in 100	☐	*or*	$16.50 for sure	☐
12)	25 in 100	75 in 100	☐	*or*	$19.50 for sure	☐
13)	25 in 100	75 in 100	☐	*or*	$21.50 for sure	☐
14)	25 in 100	75 in 100	☐	*or*	$23.50 for sure	☐
15)	25 in 100	75 in 100	☐	*or*	$25.50 for sure	☐
16)	25 in 100	75 in 100	☐	*or*	$26.50 for sure	☐
17)	25 in 100	75 in 100	☐	*or*	$27.50 for sure	☐
18)	25 in 100	75 in 100	☐	*or*	$28.50 for sure	☐
19)	25 in 100	75 in 100	☐	*or*	$29.00 for sure	☐
20)	25 in 100	75 in 100	☐	*or*	$29.50 for sure	☐
	25 in 100	75 in 100	☐	*or*	$30.00 for sure	☑

TASK 30

On this page you will make a series of decisions between two options. Option A will be a 50 in 100 chance of $30 and a 50 in 100 chance of $0. Option B will vary across decisions. Initially, Option B will be a $0.50 for sure. As you proceed down the rows, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A: Chance of $30	Option A: Chance of $0		*or*	Option B: Sure Amount	
	50 in 100	50 in 100	☑	*or*	$0.00 for sure	☐
1)	50 in 100	50 in 100	☐	*or*	$0.50 for sure	☐
2)	50 in 100	50 in 100	☐	*or*	$1.00 for sure	☐
3)	50 in 100	50 in 100	☐	*or*	$1.50 for sure	☐
4)	50 in 100	50 in 100	☐	*or*	$2.50 for sure	☐
5)	50 in 100	50 in 100	☐	*or*	$3.50 for sure	☐
6)	50 in 100	50 in 100	☐	*or*	$4.50 for sure	☐
7)	50 in 100	50 in 100	☐	*or*	$6.50 for sure	☐
8)	50 in 100	50 in 100	☐	*or*	$8.50 for sure	☐
9)	50 in 100	50 in 100	☐	*or*	$10.50 for sure	☐
10)	50 in 100	50 in 100	☐	*or*	$13.50 for sure	☐
11)	50 in 100	50 in 100	☐	*or*	$16.50 for sure	☐
12)	50 in 100	50 in 100	☐	*or*	$19.50 for sure	☐
13)	50 in 100	50 in 100	☐	*or*	$21.50 for sure	☐
14)	50 in 100	50 in 100	☐	*or*	$23.50 for sure	☐
15)	50 in 100	50 in 100	☐	*or*	$25.50 for sure	☐
16)	50 in 100	50 in 100	☐	*or*	$26.50 for sure	☐
17)	50 in 100	50 in 100	☐	*or*	$27.50 for sure	☐
18)	50 in 100	50 in 100	☐	*or*	$28.50 for sure	☐
19)	50 in 100	50 in 100	☐	*or*	$29.00 for sure	☐
20)	50 in 100	50 in 100	☐	*or*	$29.50 for sure	☐
	50 in 100	50 in 100	☐	*or*	$30.00 for sure	☑

TASK 31

On this page you will make a series of decisions between two options. Option A will be a 75 in 100 chance of $30 and a 25 in 100 chance of $0. Option B will vary across decisions. Initially, Option B will be a $0.50 for sure. As you proceed down the rows, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			*or*	Option B	
	Chance of $30	Chance of $0			Sure Amount	
	75 in 100	25 in 100	☑	*or*	$0.00 for sure	☐
1)	75 in 100	25 in 100	☐	*or*	$0.50 for sure	☐
2)	75 in 100	25 in 100	☐	*or*	$1.00 for sure	☐
3)	75 in 100	25 in 100	☐	*or*	$1.50 for sure	☐
4)	75 in 100	25 in 100	☐	*or*	$2.50 for sure	☐
5)	75 in 100	25 in 100	☐	*or*	$3.50 for sure	☐
6)	75 in 100	25 in 100	☐	*or*	$4.50 for sure	☐
7)	75 in 100	25 in 100	☐	*or*	$6.50 for sure	☐
8)	75 in 100	25 in 100	☐	*or*	$8.50 for sure	☐
9)	75 in 100	25 in 100	☐	*or*	$10.50 for sure	☐
10)	75 in 100	25 in 100	☐	*or*	$13.50 for sure	☐
11)	75 in 100	25 in 100	☐	*or*	$16.50 for sure	☐
12)	75 in 100	25 in 100	☐	*or*	$19.50 for sure	☐
13)	75 in 100	25 in 100	☐	*or*	$21.50 for sure	☐
14)	75 in 100	25 in 100	☐	*or*	$23.50 for sure	☐
15)	75 in 100	25 in 100	☐	*or*	$25.50 for sure	☐
16)	75 in 100	25 in 100	☐	*or*	$26.50 for sure	☐
17)	75 in 100	25 in 100	☐	*or*	$27.50 for sure	☐
18)	75 in 100	25 in 100	☐	*or*	$28.50 for sure	☐
19)	75 in 100	25 in 100	☐	*or*	$29.00 for sure	☐
20)	75 in 100	25 in 100	☐	*or*	$29.50 for sure	☐
	75 in 100	25 in 100	☐	*or*	$30.00 for sure	☑

TASK 32

On this page you will make a series of decisions between two options. Option A will be a 90 in 100 chance of $30 and a 10 in 100 chance of $0. Option B will vary across decisions. Initially, Option B will be a $0.50 for sure. As you proceed down the rows, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A: Chance of $30	Option A: Chance of $0		*or*	Option B: Sure Amount	
	90 in 100	10 in 100	☑	*or*	$0.00 for sure	☐
1)	90 in 100	10 in 100	☐	*or*	$0.50 for sure	☐
2)	90 in 100	10 in 100	☐	*or*	$1.00 for sure	☐
3)	90 in 100	10 in 100	☐	*or*	$1.50 for sure	☐
4)	90 in 100	10 in 100	☐	*or*	$2.50 for sure	☐
5)	90 in 100	10 in 100	☐	*or*	$3.50 for sure	☐
6)	90 in 100	10 in 100	☐	*or*	$4.50 for sure	☐
7)	90 in 100	10 in 100	☐	*or*	$6.50 for sure	☐
8)	90 in 100	10 in 100	☐	*or*	$8.50 for sure	☐
9)	90 in 100	10 in 100	☐	*or*	$10.50 for sure	☐
10)	90 in 100	10 in 100	☐	*or*	$13.50 for sure	☐
11)	90 in 100	10 in 100	☐	*or*	$16.50 for sure	☐
12)	90 in 100	10 in 100	☐	*or*	$19.50 for sure	☐
13)	90 in 100	10 in 100	☐	*or*	$21.50 for sure	☐
14)	90 in 100	10 in 100	☐	*or*	$23.50 for sure	☐
15)	90 in 100	10 in 100	☐	*or*	$25.50 for sure	☐
16)	90 in 100	10 in 100	☐	*or*	$26.50 for sure	☐
17)	90 in 100	10 in 100	☐	*or*	$27.50 for sure	☐
18)	90 in 100	10 in 100	☐	*or*	$28.50 for sure	☐
19)	90 in 100	10 in 100	☐	*or*	$29.00 for sure	☐
20)	90 in 100	10 in 100	☐	*or*	$29.50 for sure	☐
	90 in 100	10 in 100	☐	*or*	$30.00 for sure	☑

TASK 33

On this page you will make a series of decisions between two options. Option A will be a 95 in 100 chance of $30 and a 5 in 100 chance of $0. Option B will vary across decisions. Initially, Option B will be a $0.50 for sure. As you proceed down the rows, Option B will change. The sure amount will increase.

For each row, all you have to do is decide whether you prefer Option A or Option B.

	Option A			*or*	Option B	
	Chance of $30	Chance of $0			Sure Amount	
	95 in 100	5 in 100	☑	*or*	$0.00 for sure	☐
1)	95 in 100	5 in 100	☐	*or*	$0.50 for sure	☐
2)	95 in 100	5 in 100	☐	*or*	$1.00 for sure	☐
3)	95 in 100	5 in 100	☐	*or*	$1.50 for sure	☐
4)	95 in 100	5 in 100	☐	*or*	$2.50 for sure	☐
5)	95 in 100	5 in 100	☐	*or*	$3.50 for sure	☐
6)	95 in 100	5 in 100	☐	*or*	$4.50 for sure	☐
7)	95 in 100	5 in 100	☐	*or*	$6.50 for sure	☐
8)	95 in 100	5 in 100	☐	*or*	$8.50 for sure	☐
9)	95 in 100	5 in 100	☐	*or*	$10.50 for sure	☐
10)	95 in 100	5 in 100	☐	*or*	$13.50 for sure	☐
11)	95 in 100	5 in 100	☐	*or*	$16.50 for sure	☐
12)	95 in 100	5 in 100	☐	*or*	$19.50 for sure	☐
13)	95 in 100	5 in 100	☐	*or*	$21.50 for sure	☐
14)	95 in 100	5 in 100	☐	*or*	$23.50 for sure	☐
15)	95 in 100	5 in 100	☐	*or*	$25.50 for sure	☐
16)	95 in 100	5 in 100	☐	*or*	$26.50 for sure	☐
17)	95 in 100	5 in 100	☐	*or*	$27.50 for sure	☐
18)	95 in 100	5 in 100	☐	*or*	$28.50 for sure	☐
19)	95 in 100	5 in 100	☐	*or*	$29.00 for sure	☐
20)	95 in 100	5 in 100	☐	*or*	$29.50 for sure	☐
	95 in 100	5 in 100	☐	*or*	$30.00 for sure	☑