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Choice Under Uncertainty in Developing Countries

by

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October 2005

Abstract. We review experimental evidence collected from risky choice experiments using poor subjects in Ethiopia, India and Uganda. Using these data we estimate that just over 50% of our sample behaves in accordance with expected utility theory and that the rest subjectively weight probability according to prospect theory. Our results show that inferences about risk aversion are robust to whichever model we adopt when we estimate each model separately. However, when we allow both models to explain portions of the data simultaneously, we infer risk aversion for subjects behaving according to expected utility theory and risk seeking behavior for subjects behaving according to prospect theory. We conclude that the current practice of designing policies under the assumption that one or other explains all behavior is fundamentally flawed.

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How do individuals in developing countries make choices under uncertainty? Economic theory now provides a rich array of theories to explain this type of behavior. To answer this question we evaluate two competing theories using data collected from artefactual field experiments[1] conducted in three developing countries (India, Ethiopia and Uganda). Our data consists of real choices from 531 subjects in very poor locales, along with information on individual demographic characteristics.

Our primary objectives are to assess the weight of evidence for the two major received theories of choice under uncertainty, expected utility theory (EUT) and prospect theory (PT), and to assess whether they lead to different inferences about the risk attitudes of our subjects. The importance for development policy of characterizing choice behavior, and hence risk attitudes, is well established. Welfare evaluation of any proposed policy with uncertain outcomes should take into account the aversion that some individuals may have to risk, and the manner in which risk-coping strategies mitigate exposure to risks (e.g, Fafchamps [2004]).[2]

Furthermore, it is clear that producers and consumers in developing countries face extraordinarily risky environments in general (e.g., Collier and Gunning [1999]). The rural poor that make up our subject pool are no different. Fafchamps [2004; p.196] concludes a book-length treatment as follows:

> We have learned that risk affects the rural poor in numerous and profound ways. The magnitude and range of shocks that affect rural populations of the Third World is without comparison in developed economies. Perhaps the only way to describe it to people who have never been there is to compare it to a war economy: death strikes at random a large proportion of the population, especially children; the provision of health services is either non-existent or insufficient; trade with the rest of the world is difficult so that many commodities are rationed or unavailable and local prices are erratic; food is at times very scarce; and steady wage employment is non-existent so that people must make a living from

[1] Our experiments are "artefactual field experiments" in the terminology of Harrison and List [2004]. That is, they involve taking procedures from the laboratory and applying them in the field.

[2] There are many examples of the importance of assessing risky choice behavior in a development context. Two directly motivated our research. First, it is well known that the impacts of trade policies have stochastic impacts on households when one accounts for the uncertainty of calibrating policy simulation models (e.g. Harrison, Rutherford and Tarr [1993, p.211ff.]). Unless one is willing to assume households are risk neutral, the welfare implications of such "policy lottery" reforms should take risk attitudes into account. Similarly, the design of schemes to compensate risk-averse households that lose from trade reforms in developing countries may be dramatically easier if the compensation is non-stochastic and the impacts of the policy reform stochastic (e.g. Harrison, Rutherford and Tarr [1993]).Of course the efficient design of such compensation schemes presumes that one knows something about the risk attitudes of different households within a country. Second, Humphrey and Verschoor [2004a] discuss how the profit performance of micro-credit and joint liability payment schemes depend on whether decision-makers are expected utility maximizers or whether they subjectively evaluate risks as in the manner postulated in prospect theory.

> self-employment in little jobs. To deal with such a harsh environment, people are equipped with very little in terms of advanced technology and accumulated assets. Financial institutions are either absent or inefficient and expensive, and in many places, inflation is rife so that the cost of hoarding money is high.

Thus it is a high priority to obtain accurate characterizations of the risk attitudes of the rural poor. To do so, as we will show, one must also obtain an accurate characteriztion of the manner in which choices under uncertainty are made.

Our analysis builds on an experimental tradition started in India by Binswanger [1980][1981][1982] and continued in Zimbabwe by Barr [2003], in Chile and Peru by Barr and Packard [2003][2005], in India, Ethiopia and Uganda by Humphrey and Verschoor [2004a][2004b], and in Timor-Leste by Botelho, Harrison, Pinto, Rutström and Veiga [2005]. Humphrey and Verschoor [2004a][2004b] conclude that the behavior they observed is inconsistent with expected utility maximization, and exhibits subjective probability weighting. They recommend that models of choice under uncertainty in developing countries should replace EUT with a version of PT. This model could then be used in conjunction with the experimental data to evaluate and quantify specific features of behavior such as attitudes towards risk.

This conclusion echoes calls made on the basis of data collected from numerous experiments conducted in the developed world (e.g. Camerer [1998]). However, it is founded on a questionable premise: that the research agenda should establish the single best account of behavior, and that "best" should be defined in terms of the model that explains the data most accurately. What if some subjects are best characterized by one model of choice under uncertainty, and other subjects are best characterized by another model of choice under uncertainty, and the two models imply different risk attitudes? It is clear that such a scenario makes it more difficult to inform policy interventions than when one assumes just one model of choice.

To investigate this possibility, and contrary to the approach adopted in conventional studies of risky choice, we take the major competing models of risky choice in the literature *and allow the data to determine the fraction of behavior described by each model.* Using a "finite mixture model" approach, we estimate the parameters of each competing model and contrast the results with those emerging from conventional estimates that assume either EUT or PT describe behavior, but not both.

We conclude that there is, in fact, support for each model in our data, so that there is no single, correct model that explains all of the data. Furthermore, as conjectured above, we show that the inferences about parameters of each model differ when one estimates the flexible specification that allows the data to determine the fraction of the choices explained by each model. In particular, our data point to a concave (risk averse) utility of income function if you assume EUT, but a convex (risk seeking) utility of income function if you assume PT. These results are consistent with the views of Humphrey [2000] and Harrison and Rutström [2005], who argue that it may be inappropriate to search for a single model of risky choice because behavior is sufficiently heterogeneous that it cannot be described by a single theory. Moreover, this is not the sort of heterogeneity that one can assume to be correlated with observable characteristics of the individuals, although the statistical approach we employ does allow for that.

We review the design of the experimental tasks in section 1. Each subject made 8 choices between pairs of lotteries with real monetary consequences, with outcomes that were substantial in terms of their income and wealth. Each subject was given these experimental tasks as part of a larger household survey, so we also have a set of characteristics to describe the individual and their household. In section 2 we specify statistical models for these data which allow choices to be made consistently with EUT or PT. We consider all binary choices jointly in order to characterize the decision processes used by our subjects across a range of tasks. The parameters of each theory are allowed to be linear functions of observed individual characteristics, as well as experimental treatments and locations, so we do not assume that every subject has the same utility function or probability weighting function. In section 2 we also specify a finite mixture model in which observed choices can may be generated by either EUT decision-makers or PT decision-makers. Section 3 presents out results and section 4 concludes.

1. Experiments

The experimental design provided subjects with an array of choices over monetary lotteries, just as one finds in traditional laboratory experiments in developed countries. Table 1 summarizes the design and parameters.[3] All values here are in terms of US dollars, and are expressed in cents. We discuss the local currency equivalents, and scaling for purchasing power parity, below.

The eight tasks were all *binary* choice lotteries. In each task the subject picked either lottery A or lottery B. At the end of the experiment one of the eight tasks was selected at random for each subject and the lottery chosen in that task was played-out for real money. This procedure motivates subjects to consider each choice carefully as if it were for real money, rewards them for participation in the experiment, and controls for wealth effects. To control for possible order effects, roughly one half of the subjects had the tasks presented in one order, and the other half in reverse order.[4] Using the task numbers listed in Table 1, and using H_b (H_v) to denote a hypothetical binary choice (valuation) task not listed in Table 1, one order was H_b, H_v, H_b, H_v, 1, 5, 7, 2, 4, 3, 6 and 8. So this order starts with four hypothetical tasks, and the other order has these hypothetical tasks after the real tasks.

There were 531 subjects in all. In India there were 223 subjects, drawn from two villages (108 in Vepur and 115 in Guddi).[5] In Uganda there were 208 subjects, again drawn from two villages (107 in Sironko and 101 in Bufumbo).[6] In Ethiopia there were 103 subjects.[7] Mosley and Verschoor [2005] provide more details on these regions and descriptive characteristics of the sample. We have a

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[3] There were several additional tasks that we do not report here. After our task 6 some subjects were asked a hypothetical question about livestock losses, and some subjects were asked to place a certainty-equivalent value on the lotteries in our task 7.

[4] Harrison, Johnson, McInnes and Rutström [2005] demonstrate that order effects can be significant in such settings.

[5] The experiments in India were conducted in April 2002. One location was Vepur village, and another was Guddimalakapuru village, both in the Mahabubnagar district in the state of Andhra Pradesh. This region was in the midst of a severe drought at the time.

[6] The experiments in Uganda were conducted in October 2001. One location was Sironko township, and the other was Bufumbo sub-county, both in the Mbale district of east Uganda. During the 1990's Uganda had a sustained economic recovery following the brutal dictatorships of Amin and Obote, and was not suffering from any major disturbances at the time of the experiments.

[7] The experiments in Ethiopia were conducted in February 2002. All experiments were conducted in Mana wereda (district) in the Jimma administrative zone of the Oromiya region. At that time Ethiopia was in particularly dire economic straits, after a border war with Eritrea between 1998 and 2000, and recurrent droughts that only ended in 2003.

total of 4,248 actual choices, allowing for some missing responses. With minor variations, the task and procedures were identical across each sample.

In all cases the lotteries were presented in terms of local currency. Our statistical analysis converts the local currency units into U.S. dollars and cents using purchasing power parity (PPP) conversion rates. Thus the statistical analysis is undertaken using our best estimate of the local purchasing power of each monetary outcome. In 2000 the PPP rates for Ethiopia, India and Uganda were 8.22, 44.94 and 1644.47, in terms of the rate at which the local currency converted to one U.S. dollar.[8] The PPP exchange rates actually used for our experiments are close to these: 8.75, 50.33 and 1750, respectively, and differ due to differences in exchange rates prevailing at the exact time of each experiment. We recognize that there can be significant differences in purchasing power within regions of developing countries, reflecting differences in patterns of consumption and local prices (Deaton [1997; §5.2]). Although definitions of poverty differ, there can nonetheless be no doubt that a large fraction of our subjects were closer to absolute poverty lines than conventionally encountered in experiments of this type. The outcomes in our experiment also represented substantial amounts of money to our subjects.

2. Alternative Theories

We assume just two competing theories of choice under uncertainty to explain these data: EUT and PT. There are several major alternative theories, and many parametric variants of these theories, but we take these two theories to be major competitors in the literature.[9] We adopt relatively flexible functional forms to implement each theory.

One of the proposed models is a simple EUT specification which assumes a constant relative risk aversion (CRRA) utility function defined over the "final monetary prize" that the subject

[8] All purchasing power parity estimates are obtained from Heston, Summers and Aten [2002].

[9] Starmer [2000] provides an excellent review of the major alternatives. He concludes that if EUT is to be replaced as the dominant theory of risky choice in economics, the evidence points to Tversky and Kahneman's [1992] PT as being the best candidate. Although we reject the notion of completely replacing EUT, as explained later, we accept his view that PT should be viewed as the strongest contender.

would receive if the lottery were played out. That is, the argument of the utility function is the prize in the lottery, which is always non-negative.[10]

The other model is a popular specification of prospect theory (PT) due to Kahneman and Tversky [1979], in which the utility function is defined over gains and losses separately and a probability weighting function converts the underlying probabilities of the lottery into subjective probabilities.[11] The three critical features of the PT model are (i) that the arguments of the utility function be gains or losses relative to some reference point, taken here to be zero; (ii) that losses loom larger than gains in the utility function; and (iii) that there be a nonlinearity in the transformed probabilities. The first and second points are irrelevant here since all lottery choices were in the gain domain. We discuss the properties of the nonlinear probability weighting function below.

A. Expected Utility Specification

We assume that utility of income is defined by $U(x) = (x^{1-r})/(1-r)$ where x is the lottery prize and r is a parameter to be estimated. With this CRRA specification, $r=0$ indicates risk neutrality, $r>0$ indicates risk aversion, and $r<0$ indicates risk loving. Probabilities for each outcome k, p(k), are those that are induced by the experimenter, so expected utility is simply the probability weighted utility of each outcome in each lottery. Since there were up to 3 implicit outcomes in each lottery i, $EU_i = \sum_k [\, p(k) \times U(k) \,]$ for k = 1, 2, 3.

A simple stochastic specification is used to specify likelihoods conditional on the model. The EU for each lottery pair is calculated for a candidate estimate of r, and the difference $\nabla EU = EU_R$ -

[10] Some take the view that EUT requires that utility be defined over terminal wealth, and not income. This is false. One can define EUT over income (EUTi) or terminal wealth (EUTw), since the axioms of EUT are silent on the arguments of the utility function. One is tempted to think that this point is well-known since Markowitz [1952] and Samuelson [1952; ¶13, p.676], but that may just be a hindsight bias. Cox and Sadiraj [2005] and Rubinstein [2002] make these points quite clearly, in the context of controversies over the validity of EUT generated by Rabin [2000] and Rabin and Thaler [2001]. Whether or not one models utility as a function of terminal wealth or income depends on the setting. Both specifications have been popular. The EUTw specification was widely employed in the seminal papers defining risk aversion and the application of those concepts to portfolio choice and finance. On the other hand, the EUTi specification has been widely employed by auction theorists and experimental economists testing EUT. The central point is that either is valid, and we adopt an EUTi interpretation.

[11] We use the language of EUT, but prospect theorists would instead refer to the utility function as a "value function," and to the transformed probabilities as "decision weights."

EU_L calculated, where EU_L is the left lottery in the display and EU_R is the right lottery. A deterministic choice EUT can then be specified by assuming some cumulative probability distribution function, G(·), such as the logistic.[12] Thus the likelihood, conditional on the EUT model being true, depends on the estimates of r given the above specification and the observed choices. The conditional log-likelihood is

$$\ln L^{EUT}(r; y,X) = \sum_i l_i^{EUT} = \sum_i [(\ln \Lambda(\nabla EU) \mid y_i=1) + (\ln (1-\Lambda(\nabla EU)) \mid y_i=0)]$$

where y_i =1(0) denotes the choice of the right (left) lottery in task i, and X is a vector of individual characteristics.[13]

We allow each parameter to be a linear function of the observed individual characteristics of the subject. This is the X vector referred to above. We consider six characteristics. Four are binary variables to identify the order of the task, the country, females, and subjects that reported having some secondary education or more. We also included age in years and the number of people living in the household. The estimates of *each* parameter in the above likelihood function entails estimation of the coefficients of a linear function of these characteristics. So the estimate of r, $\hat{r}$, would actually be

$$\hat{r} = \hat{r}_0 + (\hat{r}_{ORDER} \times ORDER) + (\hat{r}_{ETHIOPIA} \times ETHIOPIA) + (\hat{r}_{UGANDA} \times UGANDA) + (\hat{r}_{FEMALE} \times FEMALE) + (\hat{r}_{EDUC} \times EDUC) + (\hat{r}_{AGE} \times AGE) + (\hat{r}_{NHHD} \times NHHD),$$

where $\hat{r}_0$ is the estimate of the constant, normalized on India in terms of countries. If we collapse this specification by dropping all individual characteristics, we would simply be estimating the constant terms for each of r and μ.

The estimates allow for the possibility of correlation between responses by the same subject, so the standard errors on estimates are corrected for the possibility that the 8 responses are clustered

[12] One could extend this analysis to include a stochastic specification of errors conditional on each theoretical model. There are several alternative specifications: see Harless and Camerer [1994], Hey and Orme [1994] and Loomes and Sugden [1995] for the first wave of empirical studies including some formal stochastic specification in the version of EUT tested. There are several species of "errors" in use, reviewed by Loomes and Sugden [1995]. Some place the error at the final choice between one lottery or the other after the subject has decided deterministically which one has the higher expected utility; some place the error earlier, on the comparison of preferences leading to the choice; and some place the error even earlier, on the determination of the expected utility of each lottery.

[13] The pedagogic designation of "left" or "right" is arbitrary, as long as the lotteries are evaluated consistently in the likelihood function.

for the same subject. The use of clustering to allow for "panel effects" from unobserved individual effects is common in the statistical survey literature.[14] Our estimates also allow for the stratification of observations by village (and hence also country).

B. Prospect Theory Specification

There are two components to the PT specification, the utility function and the probability weighting function.

We use the same CRRA functional form as specified for EUT: $U(x) = (x^{1-\alpha})/(1-\alpha)$. We do not have any losses in the lotteries considered here, so we drop the part of the utility function in PT that is defined for losses.[15]

There are two variants of PT, depending on the manner in which the probability weighting function is combined with utilities. The original version proposed by Kahneman and Tversky [1979] posits some weighting function which is separable in outcomes, and has been usefully termed Separable Prospect Theory (PT) by Camerer and Ho [1994; p. 185]. The alternative version, proposed by Tversky and Kahneman [1992], posits a weighting function defined over the cumulative probability distributions. In either case, the weighting function proposed by Tversky and Kahneman [1992] has been widely used. It is assumed to have well-behaved endpoints such that $w(0)=0$ and $w(1)=1$ and to imply weights $w(p) = p^{\gamma}/[\, p^{\gamma} + (1-p)^{\gamma}\,]^{1/\gamma}$ for $0<p<1$. The normal assumption, backed by a substantial amount of evidence reviewed by Gonzalez and Wu [1999], is that $0<\gamma<1$. This gives the weighting function an "inverse S-shape," characterized by a concave section signifying

[14] Clustering commonly arises in national field surveys from the fact that physically proximate households are often sampled to save time and money, but it can also arise from more homely sampling procedures. For example, Williams [2000; p.645] notes that it could arise from dental studies that "collect data on each tooth surface for each of several teeth from a set of patients" or "repeated measurements or recurrent events observed on the same person." The procedures for allowing for clustering allow heteroskedasticity between and within clusters, as well as autocorrelation within clusters. They are closely related to the "generalized estimating equations" approach to panel estimation in epidemiology (see Liang and Zeger [1986]), and generalize the "robust standard errors" approach popular in econometrics (see Rogers [1993]). Wooldridge [2003] reviews some issues in the use of clustering for panel effects, in particular noting that significant inferential problems may arise with small numbers of panels.

[15] To be accurate, *we* did not frame any of the prizes as negative numbers, which would make them losses relative to a reference point of zero. If the subject came into the experiment expecting some average level of earnings per task, prizes that implied a lower earning might be *subjectively* framed as a loss. We assume that this is not the case, and that all subjects implicitly used zero as their reference point.

the overweighting of small probabilities up to a crossover-point where w(p)=p, beyond which there is then a convex section signifying underweighting. If $\gamma>1$ the function takes the less conventional "S-shape," with convexity for smaller probabilities and concavity for larger probabilities.

Assuming that PT is the true model, prospective utility PU is defined in much the same manner as when EUT is assumed to be the true model. The PT utility function is used instead of the EUT utility function, and w(p) is used instead of p, but the steps are otherwise identical. The difference in prospective utilities is defined similarly as $\nabla PU = PU_R - PU_L$. Thus the likelihood, conditional on the PT model being true, depends on the estimates of α and γ given the above specification and the observed choices.[16] The conditional log-likelihood is

$$\ln L^{PT}(\alpha, \gamma; y,X) = \sum_i l_i^{PT} = \sum_i [(\ln \Lambda(\nabla PU) \mid y_i=1) + (\ln (1-\Lambda(\nabla PU)) \mid y_i=0)].$$

The parameters α and γ can again be estimated as linear functions of the vector X.

C. A Mixture Model Specification

If we let π^{EUT} denote the probability that the EUT model is correct, and $\pi^{PT} = (1-\pi^{EUT})$ denote the probability that the PT model is correct, the grand likelihood can be written as the probability weighted average of the conditional likelihoods. Thus the likelihood for the overall model estimated is defined by

$$\ln L(r, \alpha, \gamma, \pi^{EUT}; y,X) = \sum_i \ln [(\pi^{EUT} \times l_i^{EUT}) + (\pi^{PT} \times l_i^{PT})].$$

This log-likelihood can be maximized to find estimates of the parameters. Just as we allowed the parameters for EUT and PT to be estimated as linear functions of the observables X, we could do so in this case. However, the sample is not sufficiently large to allow robust estimation of the mixture model with the full set of covariates, so we restrict analysis to including the country dummies for π^{EUT}.

[16] The fact that the PT specification has three more parameters than the EUT specification is meaningless. One should not pick models on some arbitrary parameter-counting basis.

3. Results

A. Estimates of the EUT Specification

Table 2 collates the estimates from our data assuming that EUT is the sole theory explaining behavior. Panel A presents estimates assuming no covariates, and panel B extends this by including covariates. Figure 1 displays the predicted distribution of risk attitudes, using the estimated model that includes covariates. This distribution reflects the predicted values of the CRRA coefficient r, where the prediction depends on the characteristics of the individual, the location of the experiments, and the order in which the tasks were presented. These results point to moderate risk aversion over these stakes, with virtually no evidence of any risk loving behavior in the sample as a whole. In Panel A the coefficient of CRRA is estimated to be 0.536, remarkably close to estimates obtained with comparable experiments and statistical methods in developed countries.[17]

From Panel B we observe that, compared to the model with no-covariates, estimated risk aversion is slightly higher on average in India (0.841), which is the implicit country captured by the constant term. It is 0.050 higher in Ethiopia, but this effect only has a *p*-value of 0.502; but it is 0.169 higher in Uganda, and this effect has a *p*-value of 0.015. The order of experimental tasks had a mild effect on elicited risk attitudes. Women appear to be slightly less risk averse than men, although the quantitative effect is small (-0.085) and barely significant (*p*-value=0.068). There is a statistically significant effect from age, but it is quantitatively small: every 10 years of age is associated with a decline in risk aversion by 0.06.

B. Estimates of the PT Specification

Table 3 collates estimates of the data assuming that PT is the sole model explaining the data, and that we use the probability weighting function proposed by Tversky and Kahneman [1992]. Again, Panel A shows estimates that apply one model to all subjects, and Panel B includes covariates for each parameter. From Panel A we see that the estimates of risk attitudes are considerably lower

[17] For example, Holt and Laury [2002] and Harrison, Johnson, McInnes and Rutström [2005] for college students in the United States, and Harrison, Lau, Rutström and Sullivan [2005] for the adult population in Denmark.

than under EUT (α=0.464 < 0.536=r), although still consistent with risk aversion since α>0. The explanation, of course, is that probability weighting is allowed, and that substitutes for some of the concavity of the utility function when explaining the data. The estimate of γ from Panel A of Table 3 is 1.384. This implies an S-shaped probability weighting function which would entail underweighting of low probabilities and overweighting of large probabilities. This result contrasts starkly with the empirical claims from data collected in experimental laboratories in developed countries (see Gonzalez and Wu [1999]). The left panel in Figure 2 illustrates the function implied by this estimate: it clearly has underweighting for probabilities below 0.6, but the extent of overweighting for higher probabilities is not great.[18] We return to consider more flexible functions below.

Including covariates in the PT specification leads to qualitative conclusions about risk attitudes that are similar to those obtained under EUT. Subjects in Ethiopia are estimated to be slightly more risk averse than those in India (+0.033), but the effect is not statistically significant (*p*-value=0.792). However, those in Uganda are estimated to be much more risk averse on average (+0.195), and the effect is significant (*p*-value=0.045). Women are again slightly less risk averse than men, and the effect is barely significant (*p*-value=0.144). The effect of age is roughly the same as for EUT. There does not appear to be major differences in the extent of probability weighting across countries. The size of the household does affect the average extent of probability weighting.

There are some limitations of the conventional Tversky and Kahneman [1992] probability weighting function. It does not allow independent specification of location and curvature; it has a fixed point, where p=w(p) at p=1/e=0.37 for γ<1 and at p=1-0.37=0.63 for γ>1; and it is not even increasing in *p* for small values of γ. Prelec [1998] offers a two-parameter probability weighting function that exhibits more flexibility than the Tversky and Kahneman [1992] function. The Prelec [1998] function is $w(p) = \exp\{-\eta(-\ln p^{\phi}\}$, which is defined for 0<p<1, η>0 and 0<ϕ<1. Rieger and

[18] The bottom axis of each panel in Figure 2 shows the probability that was presented to the subject in a task, and the vertical axis shows the estimated "decision weight" that the subject used. Overweighting means that the subject has a w(p) estimate that is greater than the p it corresponds to, and underweighting is the reverse situation in which w(p)<p.

Wang [2006; Proposition 2] offer a two-parameter polynomial of 3rd degree which is defined for $0 \leq p \leq 1$, unlike the Prelec [1998] function: $w(p) = p + [(3-3b)/(a^2-a+1)]\ [p^3-(a+1)p^2+ap]$, where $0<a<1$ and $0<b<1$. The parameter restrictions on a and b ensure that the function is concave for lower values of p and then convex for larger values of p. Values of b larger than 1 would allow convex and then concave shapes, which we want to allow *a priori* given the findings of Humphrey and Verschoor [2004a][2004b].[19]

Table 4 reports estimates of the PT model assuming these two alternative functional forms, and Figures 2 and 3 display the effects on the shape of the probability weighting function and elicited risk attitudes. Both of the alternatives confirm the presence of significant underweighting of probabilities over a wide range of probabilities. In fact, both of the two-parameter probability weighting functions are *weakly* well-behaved with respect to the conventional empirical wisdom that there should be a concave and then convex ("inverse-S") shape.[20] These shapes, in fact, are quite close to the original form sketched by Kahneman and Tversky [1979; p.283], which exhibited considerable under-weighting of probabilities for virtually the whole range of p.

We observe from Table 4 and Figure 3 that the implied risk attitudes are mildly sensitive to the use of the two flexible probability weighting functions. The Prelec [1998] function leads to estimates that are mid-way between those obtained with the Tversky and Kahneman [1992] function and EUT, and the Rieger and Wang [2006] function leads to estimates that are closer to EUT. These differences derive from seemingly small differences in the probability weighting functions shown in Figure 2: the Prelec [1998] function exhibits the greatest under-weighting for lower probabilities, and the Rieger and Wang [2006] function exhibits the greatest under-weighting for all probabilities.[21]

Since it matters for inferences about risk attitudes, how should one select from these two

[19] In this case b must not exceed $1+⅓\ [(a^2-a+1)/(½+|a-½|)]$ or the function becomes non-increasing (Marc Oliver Rieger; personal communication).

[20] We obtain identical estimates of a and b if we constrain the Rieger and Wang [2006] functions such that $0<b<1$.

[21] We also note, although it should not be decisive, that the Rieger and Wang [2006] function has nicer numerical properties for our data and specifications, particularly at the extremes of the parameters where all derivatives are well-defined and finite. This is true, of course, of any finite polynomial.

flexible functional forms? The Prelec [1998] function is implied by a series of properties that it is claimed that the function has to satisfy, many of which have been inferred from previous experimental tasks rather than from theoretical considerations. There is nothing wrong with this procedure, apart from the fact that it rests as a logical matter on those prior empirical inferences being valid.[22] The Rieger and Wang [2006] function, on the other hand, is derived as the simplest polynomial to satisfy some theoretically attractive properties, most notably that it be strictly increasing and continuously differentiable on $p \in [0,1]$. Thus it does not depend, for it's *a priori* validity, on the validity of prior empirical tests, and for our purposes is preferable.[23]

Figure 4 therefore compares directly the distribution of elicited risk attitudes in our sample under EUT or PT. These distributions are based on predictions from estimated models that include the full set of covariates for each parameter. Thus we use the predictions from the estimates shown in Panel B of Table 2, and Panel D in Table 4. Although there is a slight increase in estimates of risk aversion under PT, the results are remarkably similar.

C. Estimates of the Mixture Model

Finally, we extend the comparison of the two models to consider the mixture model that allows both to play a role in explaining observed behavior. We employ the EUT model and the PT model with the Rieger and Wang [2006] probability weighting function. Maximum likelihood estimates are reported in Table 5.

The first result is that the estimated probability for the EUT model is 0.464, and that this estimate is significantly different from 0 or 1 (p-value<0.001). A test of the null hypothesis that $\pi^{EUT}=½$ has a p-value of 0.44, and the upper and lower bounds of the 95% confidence interval for π^{EUT} are 0.36 and 0.56. Thus we *might* be inclined to conclude that the weight of the evidence

[22] Note that we are *not* saying that the choice of the Prelec [1998] weighting function implies that those empirical properties will be true.

[23] Underlying this perspective is some agnosticism with respect to assertions that previous tests of EUT provide clear conclusions that are independent of complications. From different perspectives, Harrison [1994], Humphrey [2000] and Harrison and Rutström [2005] illustrate our concerns.

supports PT over EUT by a (quantum) nose, but that would be an invalid inference for reasons explained earlier. *Instead, we conclude that the data is consistent with each model playing a roughly equal role as a data generating process.*

We believe that this finding is of more general significance. For example, Humphrey [2000; p.260] draws the following conclusion from some common consequence tests with subjects from developed countries that resonates well with our findings:

> The data are not explained by any of the generalised expected utility models which were developed to explain observed violations of expected utility theory in decision-problems of exactly the type used in this experiment. More worrying, perhaps, is that minor changes in problem representation seemingly impart large changes in choices. It is not surprising, therefore, that any single model is descriptively inadequate. Starmer [1992; p. 829] suggests that individual choice behaviour is 'more subtle and complex' than decision theorists have generally conveyed in their models. If so, this may render the induction of theories from sub-sets of experimental evidence problematic. [...]
>
> This conclusion depends upon the perceived role of theory. If a *single* theory should explain as much (as parsimoniously) as possible, the volumes of diverse observed influences on decision-making behaviour seemingly condemn this task to inevitable failure. If, however, risky choice is recognised as being too complex to be captured by any single theory and that the role of a single theory is to capture a *facet* of behaviour in a *specific* context, then it may be necessary to accept that slightly different contexts will invoke additional facets of behaviour and overall explanations of data will require more than one model. Although the behaviour observed in this experiment *might*, with sufficient ingenuity, be explained by a single model involving a complex probability weighting function, experience suggests that any such function will be limited in its application to other types of decision problem.

Our results are also consistent with more elaborate mixture models applied to larger databases of choice under uncertainty by Harrison and Rutström [2005].

The second result from Table 5 is that the estimated risk attitudes and shape of the estimated probability weighting function change significantly under PT. In fact, the sample exhibits significant *risk loving* behavior to the extent that it follows the PT data generating process (α = -0.195), but remains risk averse to the extent that it follows the EUT data generating process (r = +0.796). The effect of allowing for the mixture model estimates on the probability weighting function are illustrated in Figure 5. The panel on the left shows the estimated function when PT was assumed to be the sole data generating process, and "had to" explain 100% of these data.[24] The panel on the right of Figure 5 shows the estimated function when PT only has to account for 54% of these data, and EUT is allowed to explain the other 46% of these data. It exhibits the same qualitative shape as

[24] The panel on the left of Figure 5 is the same function shown on the far right panel of Figure 2.

the function estimated conditional on PT being the sole data generating process, but with a marked increase in the underweighting of probabilities.

These results also force one to pay attention to the choice of parametric models for utility and probability weighting. The Reiger and Wang [2006] function is actually "well-behaved" with the parameter values in Table 5: even though it has a proximately flat region for probabilities between 0.2 and 0.4, it is strictly increasing, weakly concave for the lowest probabilities, and then sharply convex for most of the probabilities used in the lotteries.

We also extended the mixture model to include binary dummies for Ethiopia and Uganda for the π^{EUT} parameter. The results indicate that there is least support for the EUT model on average in India (0.35) than in Ethiopia (0.57) or Uganda (0.51). We can reject the hypothesis that the EUT and PT models have equal explanatory power in India (*p*-value=0.014), but not in Ethiopia (*p*-value=0.38) or Uganda (*p*-value=0.85). However, even in the case of India, the 95% confidence intervals for the support of the EUT model are between 0.23 and 0.47.

The changes in results under PT are striking as we move from the original specification to the mixture model. Consider the underweighting of probabilities. Underweighting means that when subjects are told that some outcome has a 50% chance of occurring that they behave as if it has much less chance of occurring. This appears to be true for all of the probabilities in our lotteries, which range from ¼ to ¾. One possible explanation for this observation is that our mixture model estimates reflect the *pessimism* of PT subjects. Our subjects might behave pessimistically because of the general economic conditions prevailing at the time of the experiments. As noted earlier, the regions we visited in India and Ethiopia were experiencing droughts. If this served to engender a general pessimism about uncertain events, this might account for our results.

Another possible explanation for underweighting is that it reflects subjects not believing that the random process was actually fair, despite the fact that we used no deception whatsoever, used transparent physical randomization devices, and saw no evidence that our subjects were concerned with being cheated. However, if the subjects believe that the experimenter had a way of making the outcome actually go against them, then one might expect to see behavior of this kind. Such concerns are always a part of any experiment, of course, and are the reason that many experimental economists use physical randomizing devices rather than rely on computers whenever possible. But it is distinctly possible that cultural beliefs about certain physical randomizing devices, and experiences with being "cheated" in such interactions, are different in developing countries.[25]

Now consider the *qualitative* change in risk attitudes under the PT model when one moves from assuming it to be the only data-generating process to being one of two possible data-generating process. One might ask if this result is an artefact of the use of a mixture model. Intuitively, if EUT can explain about 50% of the sample data, and if all of these subjects happen to be risk averse, one might ask whether mixture model simply assigns the risk loving subjects to the PT model since there is no alternative model for them to be assigned to. Thus what appears to be a change in risk attitudes under PT is, according to this view, just due to the risk lovers being "residually" assigned to the PT model. Although difficult to state formally, this is a good question, which goes to the heart of the use of statistical models to simultaneously identify parameters *and* alternative models. This question is in effect a comment on the potential dangers of assuming that the EUT decision-maker and the PT decision-maker are each homogenous: they can have different risk attitudes in the specification estimated in Table 5, but if you are an EUT decision-maker you have to have the same risk attitude as every other EUT decision-maker.

A complete response to this question would require that one include individual characteristics of the respondents in the parameters of the mixture model, to identify any heterogeneity *within* the subset of EUT or PT decision-makers. We do this with respect to the risk

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[25] The outcomes in our experiment were substantial and, in terms of PPP, above those typically offered in experiments in developed countries. In experiments similar to ours, but conducted in developed countries, large incentives might be considered an attractive design feature: they motivate careful consideration of decisions and may offset some "induced" risk seeking stemming from subjects "gambling with the house money." In our experiments large incentives may have induced the underweighting of probabilities if subjects believed that the opportunity to gamble with such large sums of "house money" was too good to be true. Such belief may have undermined confidence in the authenticity of the random devices employed to resolve risk. This possibility is likely to be mitigated in developed countries where experimental subjects, who are usually undergraduate students, are immersed in an environment where being paid non-trivial sums to complete simple experimental tasks for research purposes is likely to be viewed less suspiciously.

aversion coefficient under PT, α. The average value for this coefficient is -0.16, consistent with the estimate from the homogenous-PT model in Table 5. But these estimates show a significant variation in the risk attitudes within the subset of PT decision-makers. Those in India are the most risk-loving on average (-0.32), with those in Uganda being risk-neutral on average (0.03), and those in Ethiopia being in-between and risk-loving (-0.16).[26] The presence of some secondary education is associated with a significantly higher aversion to risk at the margin (+0.14, with a *p*-value of 0.045), and there is a dramatic effect of age. Every additional year lowers risk aversion by 0.033, and this a marginal effect that is statistically significant (*p*-value=0.002). The effect of age can be seen in Figure 6, which stratifies the predicted risk aversion coefficient α under PT for each subject. Younger subjects tend to be risk averse under PT, and older subjects tend to be risk loving under PT. Whether or not the same effect is observed under EUT, Figure 6 dramatically illustrates that there is considerable variation in risk attitudes *within the subset of PT decision-makers*.

By way of contrast, Figure 7 shows a comparable display of the association of age on risk attitudes *within the subset of EUT decision-makers*. Although there is a similarly declining marginal effect on risk attitudes (-0.005 per year of age), the effect is not statistically significant (*p*-value=0.56). Thus we see that there is considerable sensitivity of the demographic pattern of risk attitudes to the type of choice theory that best explains behavior. Thus reliable policy inferences about age and risk attitude should condition on the heterogeneity of the type of decision-making model being used as well as the observable characteristic age.[27]

Of course, there are many extensions of our approach possible before one can draw definitive conclusions. More data always helps, but for statistical inferences based on mixture models it is more than normally true since one is remaining "agnostic" about which data generating process

[26] These estimates are average effects, including variations in age and sex, for example, in each country.

[27] For example, one of the most important risky choices that our subjects make in practice is whether or not to take up the production of lucrative but input-intensive cash crops, such as tomatoes and cabbages. Agricultural extension workers told us that it was primarily young men who gamble all on such crops, for a season or two, often to finance their eventual migration to a town or city. Our findings are certainly inconsistent with the presumption that this behavior is due to risk-loving tendencies among the young, and may have broader implications for micro-finance schemes that consider financing the growing of lucrative, input-intensive crops and for the targeting of agricultural extension.

dominates. This need for more data would only become more severe if one admitted more than two data-generating processes.[28] In addition, we would want to examine alternatives to EUT that have some theoretically attractive properties in comparison to the separable PT considered here. In this vein, it might be useful to examine some of the popular stochastic error specifications that have been proposed.

4. Concluding Remarks

Our results show how important it is to be clear about the theoretical and statistical assumptions underlying inferences from observed data. For example, our results point to the dangers of drawing inferences about risk attitudes when one incorrectly assumes that behavior is generated by only one data generating process. When we do that and assume PT or EUT, we infer risk aversion, and our inferences about the degree of risk aversion do not appear to be affected by which of the two models we adopt. But when we allow some of the data to be explained by EUT and some to be explained by PT, we infer risk aversion for the subjects following EUT and risk loving behavior for the subjects following PT. This is a general point that is true for developed countries as well as developing countries, but it is likely to be more significant in developing countries where one might expect more noise in the data due to the relative unfamiliarity of the tasks.

Substantively, we conclude that there is equal support for the two major models of choice under uncertainty considered here. It is not the case that EUT or PT wins, but that the data is consistent with each playing some roughly equal role. Thus, substituting PT for EUT would be tantamount to replacing one "half wrong" assumption with another. This conclusion implies that policies should not be designed under the assumption that one *or* other theory explains all behavior.

[28] Intuitively, the need for data is relatively less severe if the alternative models have sharply different predictions, and relatively more severe if the alternative models have similar predictions. We therefore doubt that one can easily discriminate between the competitors to EUT without significantly more controlled data, since they have many "family similarities" (Starmer [2000]).

Table 1: Experimental Design

Task Type	Task Number	Lottery A			Lottery B		
		Outcome 1	Outcome 2	Outcome 3	Outcome 1	Outcome 2	Outcome 3
Common Consequence Effect	1	250; ¼	0; ¼	100; ½	100; 1		
	2	250; ¼	0; ¾		100; ½	0; ½	
	3	250; ¾	0; ¼		250; ½	100; ½	
Cyclical Choice	4	550; ½	0; ½		250; ¾	0; ¼	
	5	250; ¾	0; ¼		250; ½	200; ¼	0; ¼
	6	550; ½	0; ½		250; ½	200; ¼	0; ¼
Preference Reversal	7	500; ¼	0; ¾		150; ¾	0; ¼	
Repeat (one of three possible tasks)	8	250; ¾	0; ¼		250; ½	100; ½	
		250; ¾	0; ¼		250; ½	200; ¼	0; ¼
		500; ¼	0; ¾		150; ¾	0; ¼	

Table 2: Maximum Likelihood Estimates of EUT Model of Choices

Coefficient	Variable	Estimate	Standard Error	*p*-value	95% Confidence Intervals	
			A. No Covariates			
r	Constant	0.536	0.024	0.000	0.488	0.583
			B. Including Covariates			
r	Constant	0.841	0.091	0.000	0.662	1.021
	Ethiopia	0.050	0.074	0.502	-0.095	0.195
	Uganda	0.169	0.070	0.015	0.032	0.306
	Order of tasks	-0.063	0.059	0.283	-0.178	0.052
	Age in years	-0.006	0.002	0.002	-0.010	-0.002
	Female	-0.085	0.046	0.068	-0.176	0.006
	Some secondary education	0.056	0.059	0.345	-0.060	0.172
	Number in household	-0.013	0.010	0.178	-0.033	0.006

Figure 1: Risk Attitudes Assuming EUT

Estimates from Ethiopia, India and Uganda

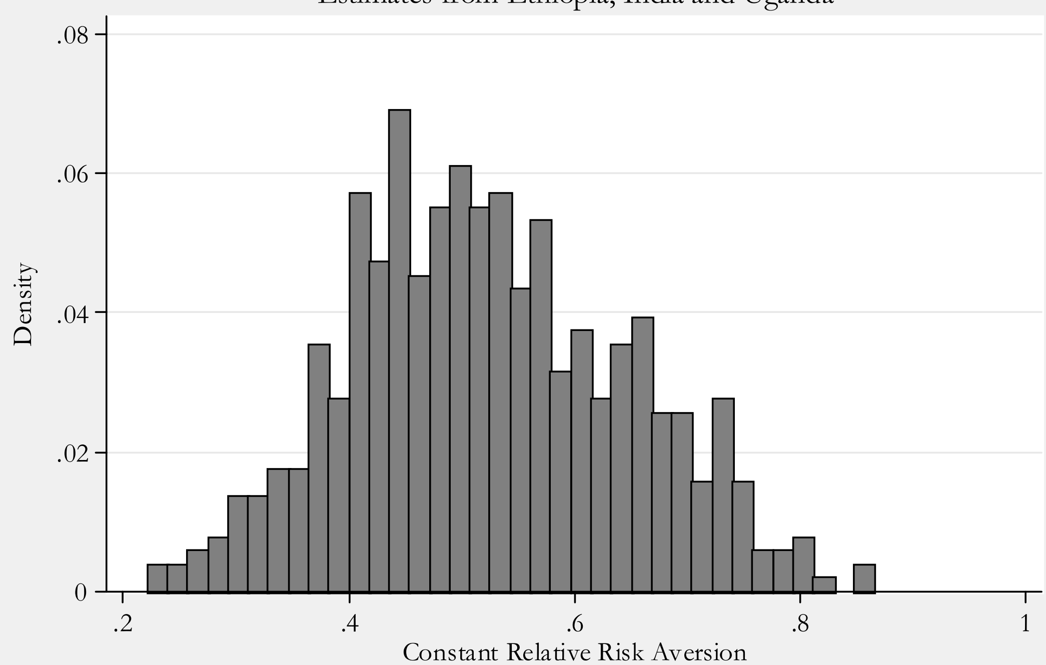


Table 3: Maximum Likelihood Estimates of PT Model of Choices With Tversky-Kahneman Probability Weighting Function

Coefficient	Variable	Estimate	Standard Error	*p*-value	95% Confidence Intervals	
			A. No Covariates			
α	Constant	0.464	0.036	0.000	0.393	0.535
γ	Constant	1.384	0.070	0.000	1.246	1.522
			B. Including Covariates			
α	Constant	0.896	0.128	0.000	0.645	1.147
	Ethiopia	0.033	0.126	0.792	-0.215	0.281
	Uganda	0.195	0.097	0.045	0.004	0.385
	Order of tasks	-0.056	0.098	0.566	-0.248	0.136
	Age in years	-0.007	0.003	0.031	-0.014	-0.001
	Female	-0.104	0.071	0.144	-0.245	0.036
	Some secondary education	0.061	0.081	0.448	-0.097	0.219
	Number in household	-0.027	0.016	0.094	-0.060	0.005
γ	Constant	0.690	0.375	0.066	-0.046	1.427
	Ethiopia	0.045	0.396	0.909	-0.734	0.824
	Uganda	0.208	0.169	0.219	-0.124	0.540
	Order of tasks	0.211	0.165	0.201	-0.113	0.535
	Age in years	0.004	0.012	0.742	-0.019	0.027
	Female	0.002	0.187	0.993	-0.366	0.370
	Some secondary education	0.076	0.159	0.634	-0.236	0.387
	Number in household	0.060	0.036	0.092	-0.010	0.131

Table 4: Maximum Likelihood Estimates of PT Model of Choices With Different Probability Weighting Function

Coefficient	Estimate	Standard Error	*p*-value	95% Confidence Intervals	
A. Tversky & Kahneman Probability Weighting Function: $w(p) = p^{\gamma}/[\ p^{\gamma} + (1-p)^{\gamma}\ ]^{1/\gamma}$					
α	0.464	0.036	0.000	0.393	0.535
γ	1.384	0.070	0.000	1.246	1.522
B. Prelec Probability Weighting Function: $w(p) = exp\{-\eta(-ln\ p^{\phi}\}$					
α	0.504	0.033	0.000	0.439	0.569
η	1.202	0.053	0.000	1.097	1.307
ϕ	0.963	0.076	0.000	0.814	1.113
C. Rieger & Wang Probability Weighting Function: $w(p) = p+[(3-3b)/(a^2-a+1)]\,[p^3-(a+1)p^2+ap]$					
α	0.546	0.025	0.000	0.496	0.596
a	0.000	†	†	†	†
b	0.775	0.048	0.000	0.680	0.870
D. Estimates of Risk Aversion Parameter α ***Using the Rieger & Wang Probability Weighting Function***					
Constant	0.823	0.102	0.000	0.622	1.024
Ethiopia	0.055	0.081	0.500	-0.104	0.213
Uganda	0.198	0.093	0.034	0.015	0.381
Order of tasks	-0.057	0.065	0.382	-0.186	0.071
Age in years	-0.006	0.002	0.012	-0.011	-0.001
Female	-0.084	0.050	0.098	-0.183	0.015
Some secondary education	0.053	0.062	0.394	-0.069	0.175
Number in household	-0.015	0.013	0.265	-0.040	0.011

† The point estimate for a is 1.60e-28. It is not possible to calculate estimates of the standard error because of the lack of numerical precision at such extreme values. Parameter a is estimated by estimating a non-linear transform $\kappa \in (-\infty, +\infty)$, where a = $1/[1+\exp(\kappa)]$. Then the point estimates and standard errors of a are recovered from the estimates for κ using the "delta method," which requires that derivatives be calculated in the neighborhood of the point estimate. For certain extreme values of these point estimates, these numerical derivatives become unstable and the estimated standard error unreliable.

Figure 2: Alternative Probability Weighting Functions

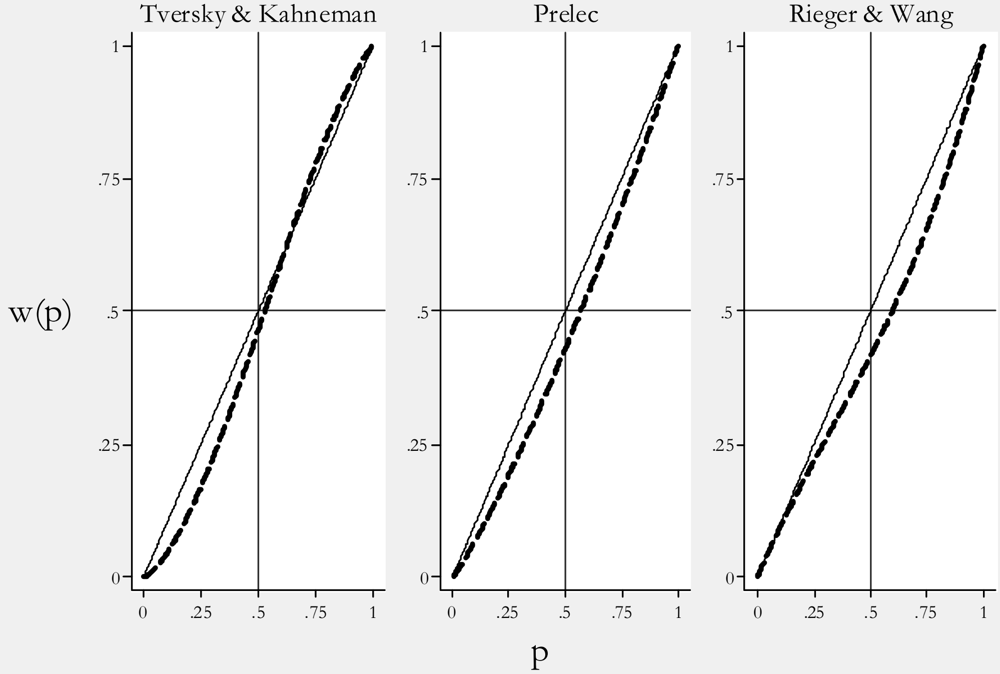
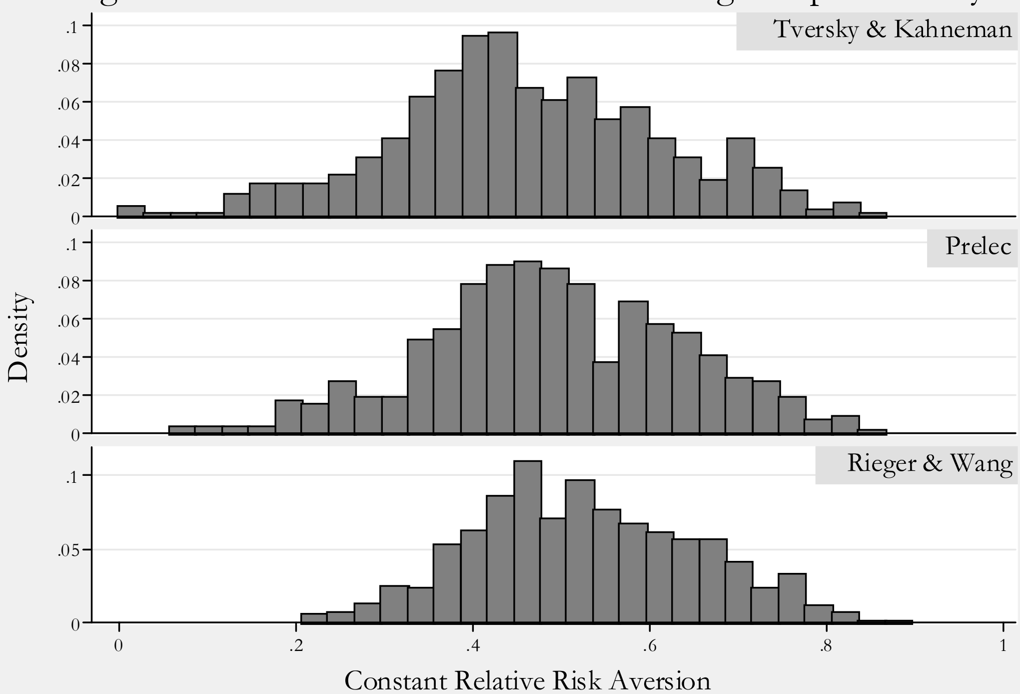


Figure 3: Alternative Risk Attitudes Assuming Prospect Theory



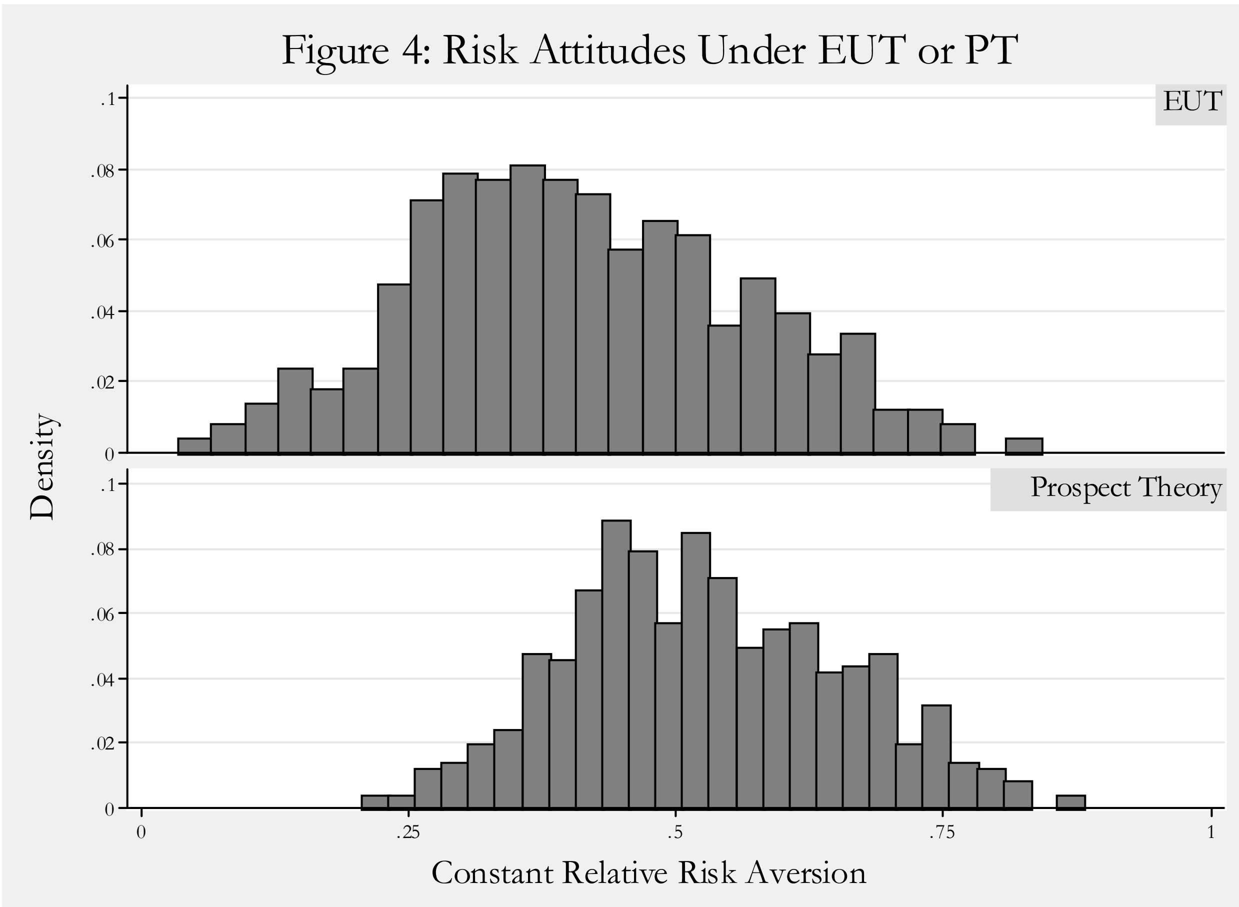


Figure 4: Risk Attitudes Under EUT or PT
EUT
Prospect Theory
Density
0
.02
.04
.06
.08
.1
0
.25
.5
.75
1
Constant Relative Risk Aversion

Table 5: Maximum Likelihood Estimates of Mixture Model

Coefficient	Estimate	Standard Error	*p*-value	95% Confidence Intervals	
α	-0.195	0.061	0.001	-0.315	-0.076
a	9.11e-08	†	†	†	†
b	4.09e-07	†	†	†	†
r	0.796	0.035	0.000	0.727	0.866
π^{EUT}	0.461	0.050	0.000	0.363	0.559

† It is not possible to calculate estimates of the standard error of a and b because of the lack of numerical precision at such extreme values. Parameter a is estimated by estimating a non-linear transform $\kappa \in (-\infty, +\infty)$, where a = $1/[1+\exp(\kappa)]$; a similar transform is used for parameter b. Then the point estimates and standard errors of a are recovered from the estimates for κ using the "delta method," which requires that derivatives be calculated in the neighborhood of the point estimate. For certain extreme values of these point estimates, these numerical derivatives become unstable and the estimated standard error unreliable.

Figure 5: Effect of Mixture Model on Probability Weighting

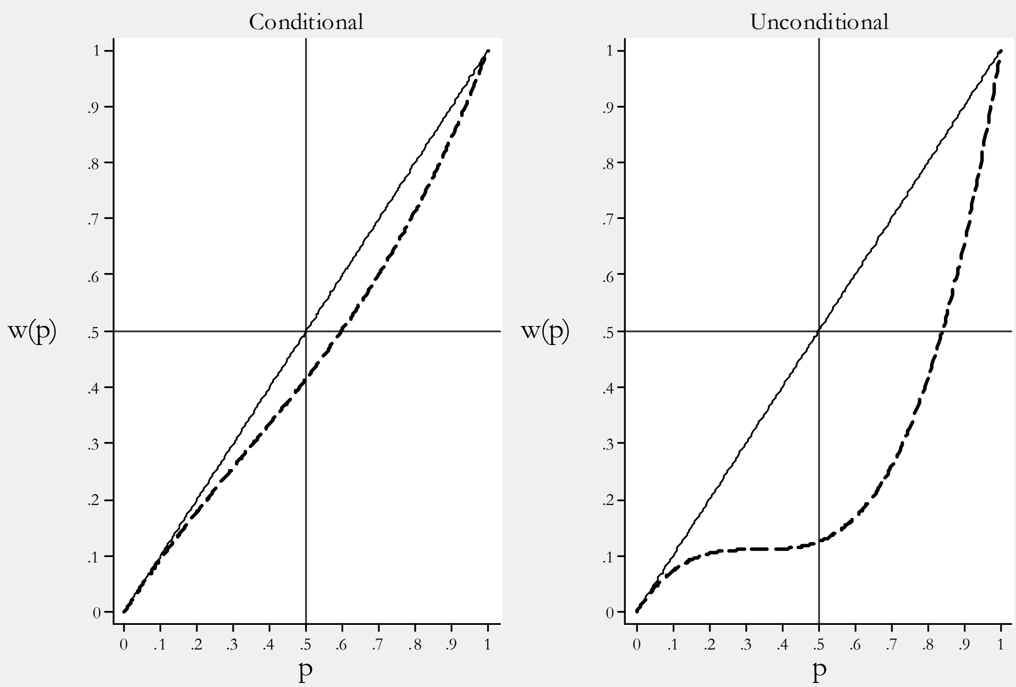


Figure 6: Effect of Age on Estimated
Risk Aversion of PT Decision-Makers

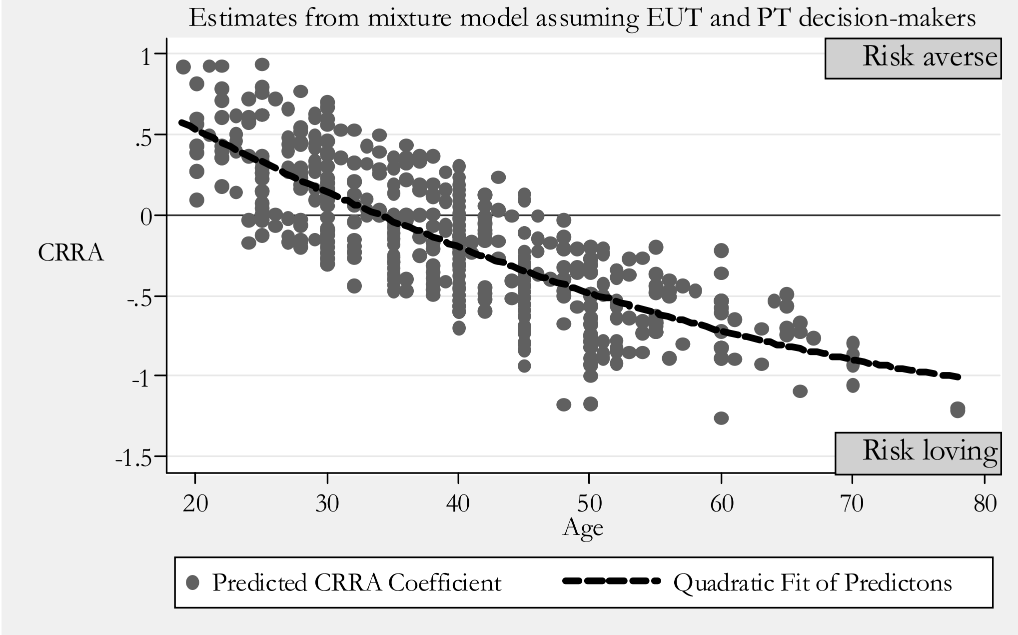
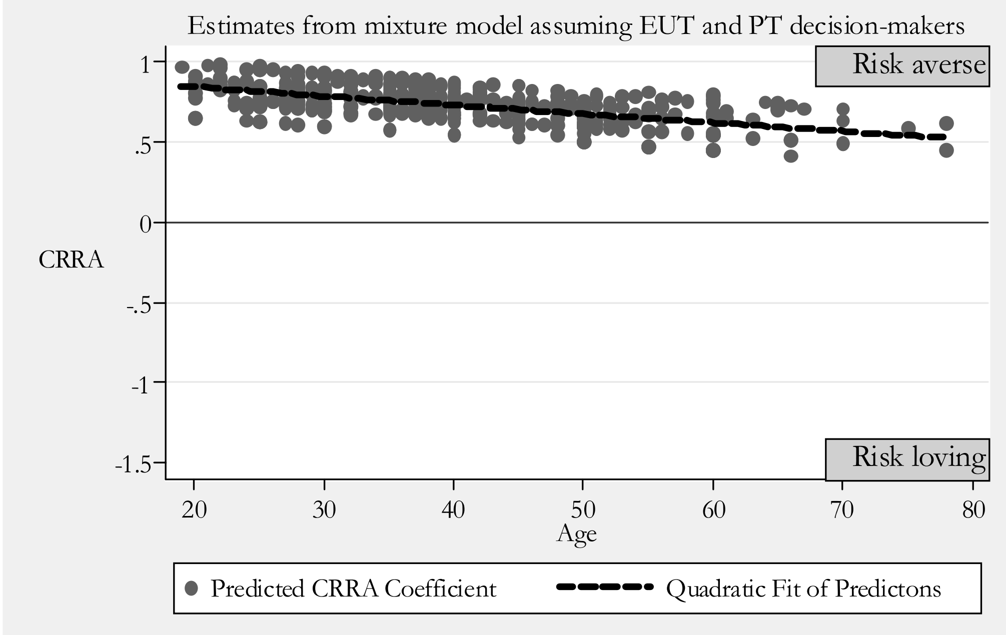


Figure 7: Effect of Age on Estimated
Risk Aversion of EUT Decision-Makers



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