Appendix A: Instructions and Parameters (Online Working Paper)

Word versions of these instructions are available in an archive at

https://cear.gsu.edu/gwh/

with a link that matches the title of this paper.

These instructions were presented in the order shown here.

Videos for each instruction were presented to subjects, to ensure that session-specific effects were minimized. The archive at the above link includes these MP4 files. The longer, main video provided images of the dice used to generate random numbers, displayed in the video as that text was read out aloud (in the video) from the instructions.

A. Introductory Text

Eye Tracking

To better understand how you make your decisions in this experiment, we will record your eye movements with an eye-tracking device. This device is essentially a camera underneath your computer screen that will tell us where you are looking on the screen at any moment. The camera is recording only information about your eye movements, and stores this information as numbers. The camera never records any image of you.

After we finish the experiment instructions, we will spend a few minutes adjusting the eye-tracking system to best record your eye movements. You will be asked to look at a series of circles on your screen so that we can focus the system to your eyes. We may also have to reposition your chair or make other minor adjustments to better configure the system.

Please let the experimenter know if you wear contact lenses, and whether they are hard or soft lenses. Sometimes we must adjust the system to account for contact lenses.

The eye-tracker can track your eyes if you wear glasses, but certain styles of glasses may create reflections which interfere with the sysem. In case you have glasses and we see reflections from them, we will first try to adjust the system to eliminate the reflections. But if the adjustments do not work, we may need to place a piece of tape on your glasses to block the reflections. Alternatively, you may instead remove your glasses if you can read the screen without glasses.

baseline

Choices Over Risky Prospects

In today's experiment you will choose between prospects with varying prizes and chances of winning. You will be presented several pairs of prospects, and for each pair you will choose the prospect you prefer. You will make choices over a number of pairs. You will actually play **one** of the prospects you choose, and you will be paid according to the outcome of that prospect, so you should think carefully about which prospect you prefer.

Making Choices

Here is an example of what the computer display of a pair of prospects will look like.

In this example, we see the left prospect has a 20% chance paying $0, a 30% chance of paying $42, and a 50% chance of paying $20. Looking now at the right prospect, we see it has a 60% chance of paying $17, and a 40% chance of paying $33.

You will select your preferred prospect by pressing on one of the two buttons on the button box in front of you. For example, if you prefer the left prospect then you would press the left button. Similarly, if you prefer the right prospect then you would press the right button. This works best if you place both hands on the button box, and then use your left hand for the left button and your right hand for the right button.

Since there is a chance that any of your choices may be played for real cash, you should approach each decision as if it is the one that you will play out.

Before each choice screen, a target will be displayed on the monitor. You must look at the target in order to move on to the choice screen. If you want to pause during the experiment, please do so on a target screen before looking at the target. This will halt the software from displaying your next choice.

Playing a prospect and getting paid

After you have worked through all the pairs of prospects, you will then play one of your selected prospects.

First, you will roll two 10-sided dice until a number comes up to determine which of your choices will be played. For example, if you had made 20 choices, you would roll until a number between 1 and 20 comes up. If instead you had made 50 choices, you would roll until a number between 1 and 50 comes up. And so on.

The experimenter will then display on your screen the corresponding choice you made. For example, if you rolled a 34, then the experimenter will display the 34th pair of prospects you saw, along with your choice. Here is an example of how the screen will look when you play a choice for cash.

Notice the blue box around the left prospect. This blue box shows that you selected the left prospect during the decision phase of the experiment. If you had selected the right prospect instead, then the blue box would have instead appeared around the right prospect. You can not change your choice at this point in the experiment.

Next you will roll the two 10-sided dice again to determine the payment you receive from the prospect you chose. Notice that the screen now displays how this roll will determine the possible payment amounts. For example, looking at the selected left prospect above, if you roll a 9, then you would be paid $0. If instead you rolled a 37, then you would be paid $42. And if instead you rolled a 73, then you would be paid $20.

Summary

- Which prospects you prefer is a matter of personal taste. Please work silently, and make your choices by thinking carefully about each prospect.

- You will select your preferred prospect in each pair by pressing the left or right button on the button box.

- If you want to pause while making decisions, please do so on a target screen **before** looking at the target.

- Your payoff in this experiment is determined by three things:
  1. by which prospect you select, the left or the right, for each of the pairs;
  2. by which prospect pair is chosen to be played out when you roll the two 10-sided dice the first time; and
  3. by the outcome of your chosen prospect when you roll the two 10-sided dice the second time.

- All payoffs are in cash, and are in addition to the $5 show-up payment that you receive just for being here.

C. Lotteries for the Standard Risk Aversion Task

The lottery parameters are listed in Table A1. Column **qid** refers to the ID for each question. The columns starting with the text **prob** refer to probabilities, and the columns starting with the text **prize** refer to monetary prizes. After the "prob" or "prize" text is a number, **1**, **2**, **3** and **4**, that refers to the 1st, 2nd, 3rd and 4th outcome in each lottery. Finally, after these numbers the letter **L** denotes the Left lottery in the display and the letter **R** denotes the Right lottery in the display.

Table A1: Parameters for the Risk Aversion Lottery Battery

See text for explanation of lottery names and variables

qid	prob1L	prob2L	prob3L	prob4L	prob1R	prob2R	prob3R	prob4R	prize1L	prize2L	prize3L	prize4L	prize1R	prize2R	prize3R	prize4R
7	0	0	0	1	0	0	.25	.75	0	0	0	52	0	0	24	64
19	.5	.05	.4	.05	0	0	.4	.6	0	30	61	94	0	0	25	33
25	.45	.1	.15	.3	.7	.1	.15	.05	5	31	42	49	14	58	70	79
28	.15	.2	.15	.5	0	.75	.2	.05	25	36	48	84	0	54	70	76
32	.3	.1	.5	.1	.3	.1	.3	.3	2	70	71	90	7	19	55	91
33	0	.3	.45	.25	0	0	0	1	0	3	28	33	0	0	0	17
35	.3	.6	.05	.05	0	0	0	1	18	43	54	76	0	0	0	36
39	0	0	.1	.9	0	0	.55	.45	0	0	22	66	0	0	52	72
41	0	0	0	1	.2	.2	.45	.15	0	0	0	54	1	15	85	91
48	.45	.1	.05	.4	0	0	.9	.1	9	12	36	57	0	0	27	74
54	0	.4	.05	.55	0	.3	.55	.15	0	8	20	94	0	3	84	88
58	0	.2	.6	.2	.25	.05	.25	.45	0	34	48	99	12	13	43	94
66	0	0	0	1	0	.6	.25	.15	0	0	0	37	0	18	55	88
72	0	0	.55	.45	.15	.05	.25	.55	0	0	13	99	30	31	49	52
76	.15	.25	.55	.05	0	0	0	1	47	71	75	91	0	0	0	70
84	.1	.75	.1	.05	0	0	.7	.3	11	47	59	81	0	0	38	62
85	0	0	0	1	.1	.1	.65	.15	0	0	0	62	27	56	71	82
87	0	.15	.05	.8	.3	.1	.55	.05	0	8	24	60	33	42	53	93
93	0	.3	.25	.45	0	.1	.25	.65	0	59	79	83	0	49	62	91
99	.55	.05	.1	.3	0	0	.95	.05	9	26	69	100	0	0	36	84
101	.15	.7	.1	.05	0	0	0	1	10	20	23	72	0	0	0	19
102	.35	.15	.35	.15	0	.1	.7	.2	16	34	38	76	0	15	26	99
111	.2	.1	.25	.45	0	0	0	1	26	63	72	100	0	0	0	71
113	.1	.1	.7	.1	0	0	.1	.9	20	44	50	70	0	0	25	48
115	.2	.05	.05	.7	.1	.3	.5	.1	8	43	56	57	36	40	43	75
116	0	0	0	1	0	0	.65	.35	0	0	0	73	0	0	63	93
117	0	0	.05	.95	.6	.15	.2	.05	0	0	23	35	33	43	50	56
128	.05	.1	.1	.75	0	0	.85	.15	16	44	52	70	0	0	58	83
130	0	.05	.15	.8	0	0	0	1	0	18	52	78	0	0	0	68
134	.05	.1	.7	.15	.3	.4	.25	.05	3	13	25	61	19	29	47	80
137	0	.3	.05	.65	0	0	.05	.95	0	65	66	89	0	0	33	85
141	.3	.15	.4	.15	0	0	.05	.95	9	35	44	57	0	0	18	34
143	0	0	.45	.55	0	.05	.45	.5	0	0	38	77	0	9	29	100
145	0	0	.9	.1	0	0	.85	.15	0	0	77	93	0	0	76	85

151	0	0	.8	.2	0	0	0	1	0	0	0	14	0	0	0	1
153	.2	.45	.05	.3	0	.25	.45	.3	39	51	77	95	0	59	62	63
154	0	.3	.1	.6	0	.6	.2	.2	0	16	66	90	0	60	64	77
159	.85	.05	.05	.05	0	.1	.05	.85	58	72	81	97	0	4	67	72
162	0	0	0	1	.55	.1	.3	.05	0	0	0	24	9	42	53	69
165	.05	.1	.8	.05	0	.25	.6	.15	36	39	43	90	0	28	44	87
170	.4	.3	.25	.05	0	.35	.25	.4	10	84	87	99	0	38	48	70
171	0	.4	.15	.45	.25	.05	.35	.35	0	34	60	95	26	35	84	85
173	0	0	.8	.2	.4	.25	.2	.15	0	0	27	94	19	33	50	92
177	0	0	.35	.65	0	.2	.25	.55	0	0	32	54	0	16	17	74
178	0	0	.4	.6	0	.5	.05	.45	0	0	47	53	0	23	42	83
181	.2	.1	.05	.65	0	.55	.4	.05	9	31	53	86	0	43	77	83
185	.05	.5	.15	.3	0	0	0	1	1	8	22	65	0	0	0	23
187	0	.35	.1	.55	.6	.05	.15	.2	0	9	46	65	24	35	70	94
194	0	0	0	1	0	0	.4	.6	0	0	0	70	0	0	60	78
197	0	.05	.1	.85	0	.35	.5	.15	0	4	32	67	0	37	58	92

Appendix B: Estimating Structural Models of Decision-Making (Online Working Paper)

We write out the formal econometric specifications for EUT and RDU models, to be applied to determine the probability that individual subjects behave consistently with EUT and RDU in a mixture model. The exposition here repeat certain equations from the main text so as to be self-contained.

A. Expected Utility

Assume that utility of income is defined by

$$U(x) = x^{(1-r)}/(1-r) \tag{B1}$$

where x is the lottery prize and $r \neq 1$ is a parameter to be estimated. For r=1 assume U(x)=ln(x) if needed. Thus s is the coefficient of CRRA: r=0 corresponds to risk neutrality, r<0 to risk loving, and r>0 to risk aversion. Let there be J possible outcomes in a lottery. Under EUT the probabilities for each outcome x_j, $p(x_j)$, are those that are induced by the experimenter, so expected utility is simply the probability weighted utility of each outcome in each lottery i:

$$EU_i = \Sigma_{j=1,J} [p(x_j) \times U(x_j)]. \tag{B2}$$

The EU for each lottery pair is calculated for a candidate estimate of r, and the index

$$\nabla EU = EU_R - EU_L \tag{B3}$$

calculated, where EU_L is the "left" lottery and EU_R is the "right" lottery as presented to subjects. This latent index, based on latent preferences, is then linked to observed choices using a standard cumulative normal distribution function $\Phi(\nabla EU)$. This "probit" function takes any argument between $\pm\infty$ and transforms it into a number between 0 and 1. Thus we have the probit link function,

$$\text{prob(choose lottery R)} = \Phi(\nabla EU) \tag{B4}$$

Even though this "link function" is common in econometrics texts, it is worth noting explicitly and understanding. It forms the critical statistical link between observed binary choices, the latent structure generating the index ∇EU, and the probability of that index being observed. The index defined by (B3) is linked to the observed choices by specifying that the R lottery is chosen when $\Phi(\nabla EU) > \frac{1}{2}$, which is implied by (B4).

Thus the likelihood of the observed responses, conditional on the EUT and CRRA specifications being true, depends on the estimates of r given the above statistical specification and the observed choices. The "statistical specification" here includes assuming some functional form for the cumulative density function (CDF). The conditional log-likelihood is then

$$\ln L(r; y, \mathbf{X}) = \Sigma_i [(\ln \Phi(\nabla EU) \times \mathbf{I}(y_i = 1)) + (\ln (1-\Phi(\nabla EU)) \times \mathbf{I}(y_i = -1))] \tag{B5}$$

where $\mathbf{I}(\cdot)$ is the indicator function, y_i =1(-1) denotes the choice of the right (left) lottery in risk aversion task i, and **X** is a vector of individual characteristics reflecting age, sex, race, and so on.

Harrison and Rutström [2008; Appendix F] review procedures that can be used to estimate structural models of this kind, as well as more complex non-EUT models. The goal is to illustrate how researches can write explicit maximum likelihood (ML) routines that are specific to different structural choice models. It is a simple matter to correct for multiple responses from the same subject ("clustering"), as needed for the pooled estimation results we present.

An important extension of the core model is to allow for subjects to make some *behavioral* errors. The notion of error is one that has already been encountered in the form of the statistical assumption that the probability of choosing a lottery is not 1 when the EU of that lottery exceeds the EU of the other lottery. This assumption is clear in the use of a non-degenerate link function between the latent index ∇EU and the probability of picking one or other lottery; in the case of the normal CDF, this link function is $\Phi(\nabla EU)$. If there were no errors from the perspective of EUT, this function would be a step function: zero for all values of $\nabla EU<0$, anywhere between 0 and 1 for $\nabla EU=0$, and 1 for all values of $\nabla EU>0$.

We employ the error specification originally due to Fechner and popularized by Hey and Orme [1994]. This error specification posits the latent index

$$\nabla EU = (EU_R - EU_L)/\mu \qquad \text{(B3}'\text{)}$$

instead of (B3), where μ is a structural "noise parameter" used to allow some errors from the perspective of the deterministic EUT model. This is just one of several different types of error story that could be used, and Wilcox [2008] provides an excellent review of the implications of the alternatives. As $\mu \rightarrow 0$ this specification collapses to the deterministic choice EUT model, where the choice is strictly determined by the EU of the two lotteries; but as μ gets larger and larger the choice essentially becomes random. When μ=1 this specification collapses to (B3), where the probability of picking one lottery is given by the ratio of the EU of one lottery to the sum of the EU of both lotteries. Thus μ can be viewed as a parameter that flattens out the link functions as it gets larger.

An important contribution to the characterization of behavioral errors is the "contextual error" specification proposed by Wilcox [2011]. It is designed to allow robust inferences about the primitive "more stochastically risk averse than," and posits the latent index

$$\nabla EU = [\ (EU_R - EU_L)/v\ ]/\mu \qquad (B3'')$$

instead of (B3′), where v is a new, normalizing term for each lottery pair L and R. The normalizing term v is defined as the maximum utility over all prizes in this lottery pair minus the minimum utility over all prizes in this lottery pair. The value of v varies, in principle, from lottery choice pair to lottery choice pair: hence it is said to be "contextual." For the Fechner specification, dividing by v ensures that the *normalized* EU difference $[(EU_R - EU_L)/v]$ remains in the unit interval. The term v does not need to be estimated in addition to the utility function parameters and the parameter for the behavioral error tern, since it is given by the data and the assumed values of those estimated parameters.

The specification employed here is the CRRA utility function from (B1), the Fechner error specification using contextual utility from (B3″), and the link function using the normal CDF from (B4). The log-likelihood is then

$$\ln L(r, \mu; y, \mathbf{X}) = \Sigma_i\ [\ (\ln \Phi(\nabla EU)\times \mathbf{I}(y_i = 1)) + (\ln (1-\Phi(\nabla EU))\times \mathbf{I}(y_i = -1))\ ] \qquad (B5'')$$

and the parameters to be estimated are s and μ given observed data on the binary choices y and the lottery parameters in **X**. The matrix **X** can also contain information on demographic characteristics of the subjects, as well as characteristics of the task.

It is possible to consider more flexible utility functions than the CRRA specification in (1), but that is not essential for present purposes.

B. Rank-Dependent Utility

The RDU model of Quiggin [1982] extends the EUT model by allowing for decision weights on lottery outcomes. The specification of the utility function is the same parametric specification (B1) considered for EUT, but with r replaced with ρ. To calculate decision weights w(·) under RDU one replaces expected utility defined by (B3) with RDU

$$RDU_i = \Sigma_{j=1,J}\ [\ w(p(x_j)) \times U(x_j)\ ] = \Sigma_{j=1,J}\ [\ w_j \times U(x_j)\ ] \qquad (B3')$$

where

$$w_j = \omega(p_j + ... + p_J) - \omega(p_{j+1} + ... + p_J) \qquad (B6a)$$

for j=1,... , J-1, and

$$w_j = \omega(p_j) \qquad (B6b)$$

for j=J, with the subscript j ranking outcomes from worst to best, and ω(·) is some probability weighting function.

We use a probability weighting function proposed by Prelec [1998] that exhibits considerable flexibility. This function is

$$\omega(p) = \exp\{-\eta(-\ln p)^{\varphi}\}, \tag{B7}$$

and is defined for $0<p\leq 1$, $\eta>0$ and $\varphi>1$. When $\varphi=1$ this function collapses to the Power function $\omega(p) = p^{\eta}$.

The construction of the log-likelihood for the RDU model the Prelec probability weighting requires the estimation of the parameters ρ, η, φ and μ.

C. Mixture Models

It is possible to extend this analysis by thinking of the observed choices as a mixture of two distinct latent data-generating processes, rather than one data-generating process (EUT) or the other (RDU). If we let π^{EUT} denote the probability that the EUT process is correct, and $\pi^{RDU} = (1-\pi^{EUT})$ denote the probability that the RDU process is correct, the grand likelihood of the EUT/RDU process as a whole can be written as the probability weighted average of the conditional *likelihoods*. If we define the likelihoods for the i^{th} observation under the EUT (RDU) model by l_i^{EUT} (l_i^{RDU}), then the grand likelihood for the overall EUT/RDU mixture model is

$$\ln L(r, \rho, \eta, \varphi\ \mu, \pi^{EUT}; y, \mathbf{X}) = \Sigma_i \ln [(\pi^{EUT} \times l_i^{EUT}) + (\pi^{RDU} \times l_i^{RDU})]. \tag{B8}$$

This log-likelihood can be maximized to find estimates of the parameters of each latent process, as well as the mixing probability π^{EUT}. The probability estimate is constrained to lie in the unit interval by estimating a parameter ζ and defining $\pi^{EUT} = 1/(1+\exp(\zeta))$ inside the likelihood function. The literal interpretation of the mixing probabilities is at the level of the observation.

This approach assumes that any one observation can be generated by both models, although it admits of extremes in which one or other criterion wholly generates the observation. One could alternatively define a grand likelihood in which observations or subjects are classified as following one model or the other on the basis of the latent probabilities π^{EUT} and π^{RDU}. El-Gamal and Grether [1995] illustrate this approach in the context of identifying behavioral strategies in Bayesian updating experiments. However, in the case of the EUT and RDU models, it is natural to view the tension between the models as reflecting different instances of the lottery choice problem: for example, 2-prize lotteries might be evaluated using EUT, but for 3-prize of 4-prize lotteries RDU might be used. Thus we do not believe it would be consistent with the EUT and RDU models to categorize *choices* as wholly driven either by EUT or RDU.

These priors also imply that we prefer not to use mixture specifications in which *subjects* are categorized as completely EUT or RDU. It is possible to rewrite the grand likelihood (B8) such that $\pi_i^{EUT} = 1$ and $\pi_i^{RDU} = 0$ if $l_i^{EUT} > l_i^{RDU}$, and $\pi_i^{EUT} = 0$ and $\pi_i^{RDU} = 1$ if $l_i^{EUT} < l_i^{RDU}$, where the subscript i now refers to the individual *subject*. The general problem with this specification is that it assumes that there is no effect on the probability of EUT and RDU from task domain. We do not want to impose that assumption, even for a relatively homogenous task design such as ours.

Additional References

El-Gamal, Mahmoud A., and Grether, David M., "Are People Bayesian? Uncovering Behavioral Strategies," *Journal of the American Statistical Association*, 90, 432, December 1995, 1137-1145.

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

Wilcox, Nathaniel T., "Stochastic Models for Binary Discrete Choice Under Risk: A Critical Primer and Econometric Comparison," in J. Cox and G.W. Harrison (eds.), *Risk Aversion in Experiments* (Bingley, UK: Emerald, Research in Experimental Economics, Volume 12, 2008).

Wilcox, Nathaniel T., "'Stochastically More Risk Averse:' A Contextual Theory of Stochastic Discrete Choice Under Risk," *Journal of Econometrics*, 162(1), May 2011, 89-104.

Appendix C: Previous Literature (Online Working Paper)

Rosen and Roisenkoetter [1976] appears to be the first eye-tracking study of choice over risky lotteries. Their motivation was to determine if choice over risky lotteries was "holistic," in the sense that the EU of each lottery is evaluated, and then the choice made on the basis of which is larger. The alternative is a "dimensional" pattern in which the utility of one lottery is compared to the utility of the other lottery one dimension at a time, and then some additive function used to evaluate which lottery to choose. In the case of risky lotteries, one of their three types of stimuli, one dimension is prizes and the other dimension is probabilities. Evaluating by dominance relations is the most common dimensional approach. The always had three attributes in each lottery: a positive payoff, a probability for that positive payoff, and a negative payoff. The probability for the negative payoff was implied as 1 minus the probability of the positive payoff. Their lottery pairs always made the dimensions interdependent, in the sense that some tradeoff was needed.[18] Six subjects were paid $1.88 an hour to participate, so incentives were not salient with respect to choices. Transitions between fixations were classified as dimensional, holistic, or other. Focusing just on the first two, 38% of the transitions were dimensional and 62% holistic (p. 750). Of course, the gamble design had been set up to favor holistic processing.

[18] One example is lottery A, with prizes +$4.29 and -$1.29, and probability for the positive prize of 0.44, compared to lottery B, with prizes +2.85 and -$2.80, and probability for the positive prize of 0.72. So a dimensional subject might see that B favors A with respect to the positive prize size, but A favors B with respect to the probability on that prize. So "knowledge about the probability cannot easily be evaluated in the absence of information about the corresponding payoffs," (p. 748) encouraging a holistic processing strategy.

Russo and Dosher [1983] extended this design to allow for gambles that favored dimensional processing as well as gambles that favored holistic processing. Each lottery had two outcomes, with one outcome always a zero payoff with the residual probability. Thus the display consisted of four numbers: a probability and non-zero payoff for one lottery, and a probability and non-zero payoff for the other lottery. Over 60 choices, in half the cases the "winning attribute" was probability (payoffs), in the sense that the other attribute was held constant across the two lotteries and one probability (payoffs) varied. Subjects were paid to participate, but rewards were not salient even though non-zero payoffs were only between $2.60 and $4.60. Subjects were first asked to choose their preferred lottery in each instance, and then asked to select the lottery with the highest EV in each instance, for 120 choices in total. Out of 10 subjects, 4 exhibited primarily holistic processing, 4 exhibited primary dimensional processing, 1 exhibited both, and 1 was essentially random.[19]

[19] Based on a minimum number of 3 fixations for each IA, subjects were allocated to holistic transitions, dimensional transitions, and unclassified transitions. The highest fraction of the first two was used to determine the type of decision-making process. For instance, subject #9 (Table 5, p.690) had 2,738 fixations, of which 37% led to dimensional transitions, 21% to holistic transitions, and 43% were unclassified; this subject was classified overall as dimensional. Most subjects classified as dimensional or holistic had a much higher fraction allocated to that type of transition.

Arieli, Ben-Ami and Rubinstein [2011] pursue the same strategy, to detect if subjects follow holistic strategies or what they call "component" procedures (which are the same as dimensional procedures in the prior literature). The display consisted of one lottery on the left with a positive payoff shown on top and the corresponding probability shown underneath, and another lottery on the right with a positive payoff on top and the corresponding probability underneath. In each case, zero was the other payoff with the implied probability. The posit that subjects that exhibit vertical eye transitions exhibit holistic processing, and subjects that exhibit horizontal eye transitions exhibit component or dimensional processing. Subjects were paid $12 to participate, with no salient rewards.[20] Transitions were the basis for determining the type of eye movement. In two sets of problems in which the EV was relatively easy to compute, a slight majority of patterns favored holistic processing for 70 subjects, and in two sets of problems in which the EV was relatively hard to compute, a slight majority of patterns favored component or dimensional processing. But in all four sets of problems the fraction of both types of processing was high (Table 1, p.72).[21]

Glöckner and Herbold [2011] consider the same general issue, but motivated by different theories of decisions under risk. They view EUT and Cumulative Prospect Theory (CPT) as both proposing holistic strategies,[22] and contrast this with the Priority Heuristic (PH) due to Brandstätter, Gigerenzer and Hertwig [2006], which is indeed dimensional and lexicographic.[23] Two additional

---

[20] Arieli et al. [2011; p.69] claim that there "is ample evidence that the lack of monetary incentives does not significantly affect participants' choices," despite clear evidence to the contrary surveyed by Harrison [2006].

[21] For the two easy sets, it was 24%, 23%, 18% and 28% and then 20%, 25%, 25% and 23%, where the first two percentages are vertical transitions and the last two percentages are horizontal transitions. For the two harder sets, it was 17%, 18%, 20% and 30% and then 16%, 18%, 33% and 28%.

[22] Prospect theory in general is actually a mix of presumed processing strategies. If one goes back to the original Prospect Theory of Kahneman and Tversky [1979], there were two processing stages presumed to be applied in sequence. One was an "editing" stage which applied dominance principles, among other heuristics, to simplify the task. This stage is clearly dimensional. If the editing stage did not lead to a clear dominance-based choice, the subject then engaged in a holistic "evaluation" phase. Sadly, the CPT of Tversky and Kahneman [1992] seems to have edited away the editing stage.

[23] The PH has some serious limitations in it's ability to account for the most basic of patterns in choice under risk: see Andersen, Harrison, Lau and Rutström [2010; §7].

process models from psychology are considered. In fact, since they restrict their lotteries to the gain domain, it is not CPT that they are considering but RDU. Their hypotheses for each theory are stated (p.77) in vague, qualitative terms. For example, one hypothesis for CPT (RDU) is that decision time should be the same for each task, and another hypothesis is that the amount of inspected information is the same for all tasks. Of course, one could imagine one subject with a sharply "inverse-S" pwf, who would effectively just be inspecting the information on the highest ranked prize and the lowest ranked prize, in contrast with someone that has a barely concave or convex "power" pwf who would care more or less equally about all prizes. Thus these hypotheses bear no relation to the variations within CPT (RDU), unless one constrains them arbitrarily.[24] Each of 18 subjects completed 40 binary choice tasks, for a fixed, non-salient payoff of _18. At least in terms of the comparison of CPT (RDU) and PH, the results, based on fixations and transitions, clearly support the former.

---

[24] This is what is done by Glöckner and Herbold [2011; p.74], who take the estimates from Tversky and Kahneman [1992] as if they apply precisely for every subject.

Fiedler and Glöckner [2012] is important because it appears to be the first eye-tracking study that provided salient rewards to lottery choice.[25] Subjects received a show-up fee of _6 as well as the outcome of playing out one of the selected choices from a battery of 50 choices. Average payoffs were low, by our standards: _6.20 in Study 1 and _9.20 in Study 2. However, the range of payoffs was quite wide: between _0 and just over _49 in each study. They extend the design of Glöckner and Herbold [2011] by varying the average EV and difference in EV across lottery pairs. Their analysis was agnostic about specific models of choice under risk, but focused on the dynamics of choice and how it varied with probability, payoff value, and their interaction. They regress the number of fixations on each of these covariates over all subjects (21 and 37 in Study1 and Study 2, respectively), allowing for random effects to capture unobserved heterogeneity of individuals. These results (Table 4, p.7) show that "attention to an outcome of a gamble increases with its probability and its value and that attention shifts towards the subsequently favored gamble after about two-thirds of the decision process" (p.1).

[25] Along with a closely related study by Glöckner, Fiedler, Hochman, Ayal and Hilbig [2012]. Their focus is the extent to which eye-tracking and skin-conductance measures provide more information to allow one to differentiate the cognitive processes when probabilities are "described" (i.e., shown on the interface, as in our experiments) or "experienced" (i.e., learned over time from sample realizations).

Janowski [2012; chapter II] is important because it adopts a structural approach to understanding if eye movements can explain the levels of loss aversion that subjects exhibit in their choices. An explicit, structural CPT model, of sorts, is proposed and estimated for each subject. The model assumes away any probability weighting, and assumes that the CRRA for the intrinsic utility function is the same for losses as it is for gains.[26] Subjects face an interface that shows one gain prize and probability (e.g., +$10 with probability 0.2) and one loss prize and probability (e.g., -$5 with probability 0.3). The implied probability (0.5) is applied to payoff of $0. The choice between this mixed-frame lottery was also implied: the alternative lottery was $0 for certain. There is no mention of an endowment to cover losses, so presumably this was paid out of the "show-up fee and experiment completion fee" (p. 72). Subjects were incentivized by being paid for 5 out of a staggering 384 choices, raising concerns with portfolio effects on choice.[27] The main results draw on correlations between the *point estimate* of the loss aversion parameter λ for each of 20 subjects and the percentage of time looking at the gain prize minus the percentage of time looking at the loss prize, presumably over all 384 choices. Hence these are correlations of 20 numbers with 20 numbers, which is quite a small sample. This correlation also makes no statistical sense: the point estimate of a parameter is not data, it is a random variable. Hence the finding of a positive correlation, while intuitive enough, cannot be taken seriously, quite apart from doubts about whether these estimates capture loss aversion correctly since probability weighting was assumed away.

[26] In the notation of Tversky and Kahneman [1992], it is assumed that $\alpha = \beta$.

[27] The notion of "choice" is itself unusual. Subjects were asked to indicate if the "strongly accepted the gamble," "weakly accepted the gamble," "weakly rejected the gamble," or "strongly rejected the gamble." Presumably the first two choices implied acceptance, and the last two choices implied rejection.

Su et al. [2013] also used salient rewards: 49 subjects received a show-up fee of ¥60 RMB, average salient payoffs were ¥28 RMB, and the range of payoffs was between ¥0 RMB and ¥45 RMB. Each subject made 32 choices over risky lotteries, in which there were two non-negative prizes and both probabilities were displayed. The primary hypothesis was whether cognitive processes would be different if subjects faced one realization of the lottery of choice in a pair, or faced the EV (over 100 realizations) of the lottery of choice in a pair. The latter treatment would presumably encourage holistic or "compensatory" processing, particularly since there were no dominated choices. Another treatment was to have half of their lottery pairs use computationally easy, rounded prizes and probabilities, and the other half use computationally harder prizes and probabilities. One aspect of their analysis was to compare choice predictions against the predictions of specific models, including risk-neutrality, EUT and CPT (RDU). Unfortunately the predictions for the latter two models used specific, arbitrary point estimates for structural coefficients that do not reflect the generality of the model.[28] A more interesting finding is that the fraction of transitions that are holistic rather than dimensional is much higher when the payoff metric is EV, whether or not the lottery pair values are computationally easy or hard.[29]

Stewart, Hermens and Matthews [2016] used "barely salient" rewards: subjects received £3 for participating, and a salient reward between £0 and £2.50. The lottery choice prizes ranged between £0 and £500, with an exchange rate of 1:0.005 between lab currency and actual payments (remarkably, revealed to subjects at the *end* of the experiment). Rounded lottery prizes and probabilities were selected to be computationally easy. The interface displayed one prize and probability for each lottery, with a £0 prize receiving the implied residual probability. The battery

---

[28] For EUT a log utility function is assumed, and for CPT (RDU) the "point estimates" from Tversky and Kahneman [1992] are assumed.

[29] The summary statistic used in this instance is the "search measure" SM index proposed by Böckenholt and Hynan [1994a], and discussed by Payne and Bettman [1994] and Böckenholt and Hynan [1994b].

consisted of 75 choices, with 4 of these involving stochastically dominated alternatives. The remaining choices had a median EV difference of £150, and were designed to capture a variety of "risky" and "safe" choices for various presumed levels of risk aversion. A deliberately a-theoretical analysis is adopted, using statistical models to descriptively characterize eye movements. They start by looking at fixations on attributes, and show that there is approximate balance between prizes and probabilities, irrespective of the size of each. They then focus on eye movement patterns and choice, and conclude that the simple accumulation of dwell time on a lottery better predicts the eventual choice than the patterns of dwell time. This latter result is consistent with one of the key findings of Fiedler and Glöckner [2012], that "attention shifts towards the subsequently favored gamble after about two-thirds of the decision process" (p.1).

Additional References

Andersen, Steffen; Harrison, Glenn W.; Lau, Morten, and Rutström, Elisabet, "Behavioral Econometrics for Psychologists," *Journal of Economic Psychology*, 31, 2010, 553–576.

Brandstätter, Eduard; Gigerenzer, Gerd, and Hertwig, Ralph, "The Priority Heuristic: Making Choices Without Trade-offs," *Psychological Review*, 113, 2006, 409-432.

Böckenholt, Ulf, and Hynan, Linda S., "Caveats on a Process-Tracing Measure and a Remedy," *Journal of Behavioral Decision Making*, 7, 1994a, 103-117.

Böckenholt, Ulf, and Hynan, Linda S., "Similarities and Differences Between SI and SM: A Reply to Payne and Bettman," *Journal of Behavioral Decision Making*, 7, 1994b, 123-127.

Fiedler, Susann, and Glöckner, Andreas, "The Dynamics of Decision Making in Risky Choice: An Eye-Tracking Analysis," *Frontiers in Psychology*, 3, October 2012, Article 335, 1-18.

Glöckner, Andreas; Fiedler, Susann; Hochman, Guy; Ayal, Shahar, and Hilbig, Benjamin E., "Processing Differences Between Descriptions and Experience: A Comparative Analysis Using Eye-Tracking and Physiological Measures," *Frontiers in Psychology*, 3, June 2012, Article 173, 1-15.

Glöckner, Andreas, and Herbold, Ann-Katrin, "An Eye-Tracking Study on Information Processing in Risky Decisions: Evidence for Compensatory Strategies Based on Automatic Processes," *Journal of Behavioral Decision Making*, 24, 2011, 71-98.

Janowski, Vanessa, *Computational Biases in Decision-Making*, Ph.D Thesis Dissertation, California Institute of Technology, 2012.

Payne, John W., and Bettman, James R., "The Costs and Benefits of Alternative Measures of Search Behavior: Comments on Böckenholt and Hynan," *Journal of Behavioral Decision Making*, 7, 1994, 119-122.

Rosen, Larry D., and Rosenkoetter, Paul, "An Eye Fixation Analysis of Choice and Judgment with Multiattribute Stimuli," *Memory & Cognition*, 4(6), 1976, 747-752.

Russo, J. Edward, and Dosher, Barbara Anne, "Strategies for Multiattribute Binary Choice," *Journal of Experimental Psychology: Learning, Memory and Cognition*, 9, 1983, 676-696.

Su, Yin; Rao, Li-Lin; Sun, Hong-Yue; Du, Xue-Lei; Li, Xingshan, and Li, Shu, "Is Making a Risky Choice Based on a Weighting and Adding Process? An Eye-Tracking Investigation," *Journal of Experimental Psychology: Learning, Memory and Cognition*, 39(6), 2013, 1765-1780.

Stewart, Neil; Hermens, Frouke, and Matthews, William J., "Eye Movements in Risky Choice," *Journal of Behavioral Decision Making*, 29, 2016, 116-136.

Tversky, Amos, and Kahneman, Daniel, "Advances in Prospect Theory: Cumulative Representations of Uncertainty," *Journal of Risk & Uncertainty*, 5, 1992, 297-323.

Appendix D: Detailed Estimates (Online Working Paper)

Estimates are reported for each of the models referred to in the text. Figures 2 and 3 are generated by *Stata* command files **figure2.do** and **figure3.do**, respectively, and require no data. All other estimates are generated by *Stata* command file **Main.do**. The data compilation code is included to document the procedures used, but the estimation data is provided to allow that stage to be skipped (this also ensures confidentiality of individual subjects). Data and code for replication is available in an archive at https://cear.gsu.edu/gwh/, with a link that matches the title of this paper.

Estimates of EUT Model with No Covariates

```
. ml model lf ML_eut (r: choiceR $Rdata = ) (mu: ), cluster(sid) maximize difficult init(.5 1, copy)

                                                Number of obs     =      1,000
                                                Wald chi2(0)      =          .
Log pseudolikelihood = -654.61268               Prob > chi2       =          .

                                  (Std. Err. adjusted for 20 clusters in sid)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
r            |
       _cons |   .5071636   .0326109    15.55   0.000     .4432475    .5710797
-------------+----------------------------------------------------------------
mu           |
       _cons |   .0656092   .0112976     5.81   0.000     .0434663     .087752
------------------------------------------------------------------------------
```

Estimates of RDU Model with No Covariates

```
. ml model lf ML_rdu_prelec2c (r: choiceR $Rdata = ) (LNeta: ) (LNphi: ) (mu: ), cluster(sid) maximize difficult
technique(bfgs) init(`rEUT' 0.024 -1.89 `muEUT', copy)

                                                Number of obs     =      1,000
                                                Wald chi2(0)      =          .
Log pseudolikelihood = -587.52147               Prob > chi2       =          .

                                  (Std. Err. adjusted for 20 clusters in sid)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
r            |
       _cons |   .2077079    .102424     2.03   0.043     .0069605    .4084553
```

```
-------------+----------------------------------------------------------------
LNeta        |
       _cons |   .1575808   .1045202     1.51   0.132     -.047275    .3624366
-------------+----------------------------------------------------------------
LNphi        |
       _cons |  -.5796902   .1185549    -4.89   0.000    -.8120534   -.3473269
-------------+----------------------------------------------------------------
mu           |
       _cons |   .0798412    .015685     5.09   0.000     .0490992    .1105832
------------------------------------------------------------------------------


. nlcom (eta: exp([LNeta]_b[_cons])) (phi: exp([LNphi]_b[_cons]))

         eta:  exp([LNeta]_b[_cons])
         phi:  exp([LNphi]_b[_cons])

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         eta |   1.170675   .1223592     9.57   0.000     .9308557    1.410495
         phi |   .5600719   .0663992     8.43   0.000     .4299317     .690212
------------------------------------------------------------------------------

. * test EUT
. testnl (exp([LNeta]_b[_cons])=1) (exp([LNphi]_b[_cons])=1), mtest(b)

  (1)  exp([LNeta]_b[_cons]) = 1
  (2)  exp([LNphi]_b[_cons]) = 1

---------------------------------------
       |       chi2     df       p
-------+-------------------------------
  (1)  |        1.95     1     0.3261 #
  (2)  |       43.90     1     0.0000 #
-------+-------------------------------
  all  |       54.06     2     0.0000
---------------------------------------
         # Bonferroni-adjusted p-values
```

Estimates of the EUT-RDU Mixture Model with No Covariates

```
. * mixture of EUT and RDU, with Prelec pwf
. ml model lf ML_eut_rdu_prelec2c (rEUT: choiceR $Rdata = ) (rRDU: ) (LNeta: ) (LNphi: ) (kappa: ) (mu: ) if qid_record==1,
cluster(sid) maximize technique(dfp) difficult init(`r' `rPR' `LNeta' `LNphi' 0 `mu_mix', copy)
```

```
                                                Number of obs     =      1,000
                                                Wald chi2(0)      =          .
Log pseudolikelihood = -578.39289               Prob > chi2       =          .

                                   (Std. Err. adjusted for 20 clusters in sid)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
rEUT         |
       _cons |   .4750392   .1229172     3.86   0.000     .2341258    .7159525
-------------+----------------------------------------------------------------
rRDU         |
       _cons |   .0448265   .1181319     0.38   0.704    -.1867078    .2763608
-------------+----------------------------------------------------------------
LNeta        |
       _cons |   .2211964   .1021249     2.17   0.030     .0210353    .4213576
-------------+----------------------------------------------------------------
LNphi        |
       _cons |  -.6487021   .1268583    -5.11   0.000    -.8973398   -.4000643
-------------+----------------------------------------------------------------
kappa        |
       _cons |   .2400556   .4042581     0.59   0.553    -.5522756    1.032387
-------------+----------------------------------------------------------------
mu           |
       _cons |   .0279352   .0104537     2.67   0.008     .0074463    .0484242
------------------------------------------------------------------------------

. nlcom (eta: exp([LNeta]_b[_cons])) (phi: exp([LNphi]_b[_cons])) (probEUT: 1/(1+exp([kappa]_cons))) (probRDU:
1 - (1/(1+exp([kappa]_cons))))

         eta:  exp([LNeta]_b[_cons])
         phi:  exp([LNphi]_b[_cons])
     probEUT:  1/(1+exp([kappa]_cons))
     probRDU:  1 - (1/(1+exp([kappa]_cons)))

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         eta |   1.247568   .1274078     9.79   0.000     .9978537    1.497283
         phi |   .5227238   .0663119     7.88   0.000     .3927549    .6526926
     probEUT |   .4402727   .0996224     4.42   0.000     .2450164    .6355289
     probRDU |   .5597273   .0996224     5.62   0.000     .3644711    .7549836
------------------------------------------------------------------------------

. * test EUT
. testnl (exp([LNphi]_b[_cons])=1) (exp([LNeta]_b[_cons])=1), mtest(b)
```

(1) exp([LNphi]_b[_cons]) = 1
(2) exp([LNeta]_b[_cons]) = 1

	chi2	df	p
(1)	51.80	1	0.0000 #
(2)	3.78	1	0.1040 #
all	86.69	2	0.0000

Bonferroni-adjusted p-values

Estimates of the EUT-RDU Mixture Model with Eye-Tracking Covariates Only

```
. ml model lf ML_eut_rdu_prelec2c (rEUT: choiceR $Rdata = ) (rRDU: $eyes ) (LNeta: $eyes ) (LNphi: $eyes ) (kappa: $eyes ) (mu: $eyes ) if qid_record==1, cluster(sid) maximize technique(nr) difficult continue
```

Number of obs = 1,000
Wald chi2(0) = .
Log pseudolikelihood = -558.90315 Prob > chi2 = .

(Std. Err. adjusted for 20 clusters in sid)

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
rEUT						
_cons	.9188776	.0527521	17.42	0.000	.8154853	1.02227
rRDU						
time_prob_pct	-.5973332	.2516852	-2.37	0.018	-1.090627	-.1040393
_cons	.2546193	.0328287	7.76	0.000	.1902762	.3189623
LNeta						
time_prob_pct	1.129467	.2051656	5.51	0.000	.7273496	1.531584
_cons	-.2092687	.0507628	-4.12	0.000	-.3087619	-.1097755
LNphi						
time_prob_pct	-.1122485	.3158285	-0.36	0.722	-.7312609	.5067639
_cons	-.5012057	.0685727	-7.31	0.000	-.6356056	-.3668057
kappa						
time_prob_pct	-1.85995	1.140964	-1.63	0.103	-4.096199	.376299
_cons	1.030002	.3599911	2.86	0.004	.3244328	1.735572
mu						

```
time_prob_pct |   .0377699   .0248821     1.52   0.129    -.0109982     .086538
        _cons |   .0046189   .0034282     1.35   0.178    -.0021004    .0113381
------------------------------------------------------------------------------
```

```
. nlcom (rEUT: [rEUT]_cons) (rRDU: [rRDU]_cons) (eta: exp([LNeta]_b[_cons])) (phi: exp([LNphi]_b[_cons])) (pEUT: 1/(1+exp([kappa]_cons))) (mu: [mu]_cons)

        rEUT:  [rEUT]_cons
        rRDU:  [rRDU]_cons
         eta:  exp([LNeta]_b[_cons])
         phi:  exp([LNphi]_b[_cons])
        pEUT:  1/(1+exp([kappa]_cons))
          mu:  [mu]_cons

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        rEUT |   .9188776   .0527521    17.42   0.000     .8154853     1.02227
        rRDU |   .2546193   .0328287     7.76   0.000     .1902762    .3189623
         eta |   .8111772   .0411776    19.70   0.000     .7304706    .8918838
         phi |   .6057998   .0415413    14.58   0.000     .5243804    .6872193
        pEUT |   .2630836   .0697917     3.77   0.000     .1262944    .3998729
          mu |   .0046189   .0034282     1.35   0.178    -.0021004    .0113381
------------------------------------------------------------------------------
```

```
rRDU_time_~t:  [rRDU]_cons+[rRDU]time_prob_pct - [rRDU]_cons
eta_time_p~t:  exp([LNeta]_cons+[LNeta]time_prob_pct) - exp([LNeta]_cons)
phi_time_p~t:  exp([LNphi]_cons+[LNphi]time_prob_pct) - exp([LNphi]_cons)
pEUT_time_~t:  1/(1+exp([kappa]_cons + [kappa]time_prob_pct)) - 1/(1+exp([kappa]_cons))
mu_time_pr~t:  [mu]_cons+[mu]time_prob_pct - [mu]_cons

------------------------------------------------------------------------------------
                   |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
rRDU_time_prob_pct |  -.5973332   .2516852    -2.37   0.018    -1.090627   -.1040393
 eta_time_prob_pct |    1.69861   .4575269     3.71   0.000      .801874    2.595347
 phi_time_prob_pct |  -.0643225   .1747552    -0.37   0.713    -.4068364    .2781913
pEUT_time_prob_pct |   .4332602   .2365893     1.83   0.067    -.0304463    .8969667
  mu_time_prob_pct |   .0377699   .0248821     1.52   0.129    -.0109982     .086538
------------------------------------------------------------------------------------

 ( 1)  [rRDU]time_prob_pct = 0

           chi2(  1) =    5.63
         Prob > chi2 =    0.0176
```

```
 ( 1)  [LNeta]time_prob_pct = 0
 ( 2)  [LNphi]time_prob_pct = 0

           chi2(  2) =   37.35
         Prob > chi2 =    0.0000

 ( 1)  [rRDU]time_prob_pct = 0
 ( 2)  [LNeta]time_prob_pct = 0
 ( 3)  [LNphi]time_prob_pct = 0
 ( 4)  [kappa]time_prob_pct = 0
 ( 5)  [mu]time_prob_pct = 0

           chi2(  5) =   89.57
         Prob > chi2 =    0.0000
```

Estimates of the EUT-RDU Mixture Model with Duration Covariates Only

```
. ml model lf ML_eut_rdu_prelec2c (rEUT: choiceR $Rdata = ) (rRDU: duration ) (LNeta: duration ) (LNphi: duration )
(kappa: duration ) (mu: duration ) if qid_record==1, cluster(sid) maximize technique(nr) difficult continue

                                                  Number of obs     =      1,000
                                                  Wald chi2(0)      =          .
Log pseudolikelihood = -574.75976                 Prob > chi2       =          .

                                     (Std. Err. adjusted for 20 clusters in sid)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
rEUT         |
       _cons |    .469195   .1205272     3.89   0.000      .232966    .7054241
-------------+----------------------------------------------------------------
rRDU         |
    duration |   .0083107   .0095044     0.87   0.382    -.0103175     .026939
       _cons |   .0162007    .122688     0.13   0.895    -.2242634    .2566648
-------------+----------------------------------------------------------------
LNeta        |
    duration |   .0209031    .017838     1.17   0.241    -.0140588     .055865
       _cons |   .0792039   .1538802     0.51   0.607    -.2223957    .3808034
-------------+----------------------------------------------------------------
LNphi        |
    duration |   .0118867   .0184279     0.65   0.519    -.0242313    .0480046
       _cons |  -.6963666   .1648696    -4.22   0.000    -1.019505   -.3732281
-------------+----------------------------------------------------------------
kappa        |
```

```
       duration |   -.019933   .0398271    -0.50   0.617    -.0979927    .0581268
          _cons |   .4690769   .3980416     1.18   0.239    -.3110703    1.249224
-------------+----------------------------------------------------------------
mu           |
       duration |   .0014873    .001405     1.06   0.290    -.0012664     .004241
          _cons |   .0185893   .0106805     1.74   0.082    -.0023442    .0395228
------------------------------------------------------------------------------

. test duration

 ( 1)  [rRDU]duration = 0
 ( 2)  [LNeta]duration = 0
 ( 3)  [LNphi]duration = 0
 ( 4)  [kappa]duration = 0
 ( 5)  [mu]duration = 0

           chi2(  5) =    4.10
         Prob > chi2 =    0.5344

. ml model lf ML_eut_rdu_prelec2c (rEUT: choiceR $Rdata = duration ) (rRDU: duration ) (LNeta: duration ) (LNphi:
duration ) (kappa: duration ) (mu: duration ) if qid_record==1, cluster(sid) maximize technique(nr) difficult continue

                                                  Number of obs     =      1,000
                                                  Wald chi2(1)      =       0.03
Log pseudolikelihood =  -574.7524                 Prob > chi2       =     0.8695

                                    (Std. Err. adjusted for 20 clusters in sid)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
rEUT         |
       duration |   .0023899   .0145508     0.16   0.870    -.0261292     .030909
          _cons |   .4526101   .1764061     2.57   0.010     .1068606    .7983596
-------------+----------------------------------------------------------------
rRDU         |
       duration |   .0092353   .0118641     0.78   0.436    -.0140179    .0324885
          _cons |   .0112829   .1330573     0.08   0.932    -.2495047    .2720706
-------------+----------------------------------------------------------------
LNeta        |
       duration |     .01988   .0164325     1.21   0.226    -.0123271    .0520871
          _cons |   .0847411   .1575371     0.54   0.591    -.2240259     .393508
-------------+----------------------------------------------------------------
LNphi        |
       duration |    .012593    .019596     0.64   0.520    -.0258145    .0510005
          _cons |  -.7011818   .1727134    -4.06   0.000    -1.039694   -.3626697
-------------+----------------------------------------------------------------
kappa        |
```

```
    duration |   -.0215392   .0434801    -0.50   0.620    -.1067587    .0636802
       _cons |    .4763695   .3983588     1.20   0.232    -.3043995    1.257138
-------------+----------------------------------------------------------------
mu           |
    duration |    .0014064   .0015668     0.90   0.369    -.0016645    .0044772
       _cons |    .0190107   .0111298     1.71   0.088    -.0028032    .0408246
------------------------------------------------------------------------------

. test duration

 ( 1)  [rEUT]duration = 0
 ( 2)  [rRDU]duration = 0
 ( 3)  [LNeta]duration = 0
 ( 4)  [LNphi]duration = 0
 ( 5)  [kappa]duration = 0
 ( 6)  [mu]duration = 0

           chi2(  6) =    4.31
         Prob > chi2 =    0.6350
```

Estimates of the EUT-RDU Mixture Model with Eye-Tracking and Demographic Covariates

```
. ml model lf ML_eut_rdu_prelec2c (rEUT: choiceR $Rdata = $eyes age ) (rRDU: $eyes $demog ) (LNeta: $eyes $demog )
(LNphi: $eyes $demog ) (kappa: $eyes $demog ) (mu: $eyes ) if qid_record==1, cluster(sid) maximize technique(nr)
difficult continue

                                                  Number of obs   =      1,000
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -536.12719                 Prob > chi2     =          .

                                     (Std. Err. adjusted for 20 clusters in sid)
------------------------------------------------------------------------------
              |               Robust
              |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
rEUT          |
time_prob_pct |   .1671709   .5065384     0.33   0.741    -.8256261    1.159968
          age |  -.0332573   .0356052    -0.93   0.350    -.1030422    .0365276
        _cons |    1.45978   1.053639     1.39   0.166    -.6053151    3.524876
--------------+----------------------------------------------------------------
rRDU          |
time_prob_pct |  -.7010137   .3847834    -1.82   0.068    -1.455175    .0531479
       female |   .0209461   .1990424     0.11   0.916    -.3691698    .4110621
          age |   .1083011   .0263147     4.12   0.000     .0567254    .1598769
        black |  -.3004131   .2884637    -1.04   0.298    -.8657916    .2649655
        gpaHI |   .0233276   .1000555     0.23   0.816    -.1727776    .2194327
```

```
         _cons |   -1.875593    .5793301    -3.24   0.001    -3.011059   -.7401268
--------------+----------------------------------------------------------------
LNeta         |
time_prob_pct |    1.340898    .2058003     6.52   0.000     .9375367    1.744259
       female |    .0508642    .1677341     0.30   0.762    -.2778887    .3796171
          age |   -.0711763    .0194475    -3.66   0.000    -.1092928   -.0330599
        black |    .1523834    .1812677     0.84   0.401    -.2028949    .5076616
        gpaHI |   -.1095045    .0703617    -1.56   0.120    -.2474109    .0284018
        _cons |    1.168521    .4894378     2.39   0.017     .2092411    2.127802
--------------+----------------------------------------------------------------
LNphi         |
time_prob_pct |    .3067482    .3133904     0.98   0.328    -.3074857    .9209822
       female |     .019335    .0953824     0.20   0.839    -.1676111    .2062811
          age |   -.1781848    .0831917    -2.14   0.032    -.3412376    -.015132
        black |   -.1567347    .1888621    -0.83   0.407    -.5268977    .2134282
        gpaHI |   -.2332968    .0946419    -2.47   0.014    -.4187916   -.0478021
        _cons |    3.208865     1.80336     1.78   0.075    -.3256558    6.743387
--------------+----------------------------------------------------------------
kappa         |
time_prob_pct |   -.6497203    .7637626    -0.85   0.395    -2.146667    .8472268
       female |    .2576686    .4220499     0.61   0.542     -.569534    1.084871
          age |    .0814941     .094753     0.86   0.390    -.1042184    .2672065
        black |    .1190567    .5706145     0.21   0.835    -.9993272    1.237441
        gpaHI |    .5954635    .4964954     1.20   0.230    -.3776495    1.568577
        _cons |   -1.963731    2.217975    -0.89   0.376    -6.310882     2.38342
--------------+----------------------------------------------------------------
mu            |
time_prob_pct |    .0205365    .0157074     1.31   0.191    -.0102494    .0513225
        _cons |    .0032979    .0041826     0.79   0.430    -.0048999    .0114957
-------------------------------------------------------------------------------


. nlcom (rEUT: [rEUT]_cons) (rRDU: [rRDU]_cons) (eta: exp([LNeta]_b[_cons])) (phi: exp([LNphi]_b[_cons])) (pEUT: 1/(1+exp([kappa]_cons))) (mu: [mu]_cons)

         rEUT:  [rEUT]_cons
         rRDU:  [rRDU]_cons
          eta:  exp([LNeta]_b[_cons])
          phi:  exp([LNphi]_b[_cons])
         pEUT:  1/(1+exp([kappa]_cons))
           mu:  [mu]_cons

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        rEUT |    1.45978   1.053639     1.39   0.166    -.6053151    3.524876
        rRDU |  -1.875593   .5793301    -3.24   0.001    -3.011059   -.7401268
         eta |   3.217232   1.574635     2.04   0.041     .1310045     6.30346
```

```
         phi |   24.75099   44.63495     0.55   0.579    -62.73191    112.2339
        pEUT |   .8769361    .239362     3.66   0.000     .4077953    1.346077
          mu |   .0032979   .0041826     0.79   0.430    -.0048999    .0114957
------------------------------------------------------------------------------

rEUT_time_~t:  [rEUT]_cons+[rEUT]time_prob_pct - [rEUT]_cons
rRDU_time_~t:  [rRDU]_cons+[rRDU]time_prob_pct - [rRDU]_cons
eta_time_p~t:  exp([LNeta]_cons+[LNeta]time_prob_pct) - exp([LNeta]_cons)
phi_time_p~t:  exp([LNphi]_cons+[LNphi]time_prob_pct) - exp([LNphi]_cons)
pEUT_time_~t:  1/(1+exp([kappa]_cons + [kappa]time_prob_pct)) - 1/(1+exp([kappa]_cons))
mu_time_pr~t:  [mu]_cons+[mu]time_prob_pct - [mu]_cons

-----------------------------------------------------------------------------------
                   |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+---------------------------------------------------------------
rEUT_time_prob_pct |   .1671709   .5065384     0.33   0.741    -.8256261    1.159968
rRDU_time_prob_pct |  -.7010137   .3847834    -1.82   0.068    -1.455175    .0531479
 eta_time_prob_pct |   9.080556   4.966064     1.83   0.067    -.6527495    18.81386
 phi_time_prob_pct |   8.885575   12.62497     0.70   0.482    -15.85892    33.63007
pEUT_time_prob_pct |   .0547861   .1236918     0.44   0.658    -.1876453    .2972175
  mu_time_prob_pct |   .0205365   .0157074     1.31   0.191    -.0102494    .0513225
-----------------------------------------------------------------------------------

 ( 1)  [rRDU]time_prob_pct = 0

           chi2(  1) =    3.32
         Prob > chi2 =    0.0685

 ( 1)  [LNeta]time_prob_pct = 0
 ( 2)  [LNphi]time_prob_pct = 0

           chi2(  2) =   53.08
         Prob > chi2 =    0.0000

 ( 1)  [rEUT]time_prob_pct = 0
 ( 2)  [rRDU]time_prob_pct = 0
 ( 3)  [LNeta]time_prob_pct = 0
 ( 4)  [LNphi]time_prob_pct = 0
 ( 5)  [kappa]time_prob_pct = 0
 ( 6)  [mu]time_prob_pct = 0

           chi2(  6) =  186.52
         Prob > chi2 =    0.0000


     eta_age:  exp([LNeta]_cons+[LNeta]age) - exp([LNeta]_cons)
     phi_age:  exp([LNphi]_cons+[LNphi]age) - exp([LNphi]_cons)
    pEUT_age:  1/(1+exp([kappa]_cons + [kappa]age)) - 1/(1+exp([kappa]_cons))
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eta_age	-.2210313	.1639796	-1.35	0.178	-.5424254	.1003627
phi_age	-4.039665	8.994961	-0.45	0.653	-21.66946	13.59013
pEUT_age	-.0090683	.0059729	-1.52	0.129	-.020775	.0026384

eta_female: exp([LNeta]_cons+[LNeta]female) - exp([LNeta]_cons)
phi_female: exp([LNphi]_cons+[LNphi]female) - exp([LNphi]_cons)
pEUT_female: 1/(1+exp([kappa]_cons + [kappa]female)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eta_female	.1678751	.5300893	0.32	0.751	-.8710809	1.206831
phi_female	.4832169	2.148132	0.22	0.822	-3.727045	4.693478
pEUT_female	-.0306113	.0709791	-0.43	0.666	-.1697277	.1085051

(1) [rRDU]female = 0

chi2(1) = 0.01
Prob > chi2 = 0.9162

(1) [LNeta]female = 0
(2) [LNphi]female = 0

chi2(2) = 0.09
Prob > chi2 = 0.9546

(1) [rRDU]female = 0
(2) [LNeta]female = 0
(3) [LNphi]female = 0
(4) [kappa]female = 0

chi2(4) = 0.99
Prob > chi2 = 0.9118

eta_age: exp([LNeta]_cons+[LNeta]age) - exp([LNeta]_cons)
phi_age: exp([LNphi]_cons+[LNphi]age) - exp([LNphi]_cons)
pEUT_age: 1/(1+exp([kappa]_cons + [kappa]age)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eta_age	-.2210313	.1639796	-1.35	0.178	-.5424254	.1003627

phi_age	-4.039665	8.994961	-0.45	0.653	-21.66946	13.59013
pEUT_age	-.0090683	.0059729	-1.52	0.129	-.020775	.0026384

(1) [rRDU]age = 0

chi2(1) = 16.94
Prob > chi2 = 0.0000

(1) [LNeta]age = 0
(2) [LNphi]age = 0

chi2(2) = 14.60
Prob > chi2 = 0.0007

(1) [rEUT]age = 0
(2) [rRDU]age = 0
(3) [LNeta]age = 0
(4) [LNphi]age = 0
(5) [kappa]age = 0

chi2(5) = 47.35
Prob > chi2 = 0.0000

eta_black: exp([LNeta]_cons+[LNeta]black) - exp([LNeta]_cons)
phi_black: exp([LNphi]_cons+[LNphi]black) - exp([LNphi]_cons)
pEUT_black: 1/(1+exp([kappa]_cons + [kappa]black)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eta_black	.5295777	.5422456	0.98	0.329	-.5332042	1.59236
phi_black	-3.590606	9.264395	-0.39	0.698	-21.74849	14.56727
pEUT_black	-.0134356	.0618663	-0.22	0.828	-.1346913	.1078202

(1) [rRDU]black = 0

chi2(1) = 1.08
Prob > chi2 = 0.2977

(1) [LNeta]black = 0
(2) [LNphi]black = 0

chi2(2) = 2.45
Prob > chi2 = 0.2943

```
 ( 1)  [rRDU]black = 0
 ( 2)  [LNeta]black = 0
 ( 3)  [LNphi]black = 0
 ( 4)  [kappa]black = 0

           chi2(  4) =    2.87
         Prob > chi2 =    0.5791

   eta_gpaHI:  exp([LNeta]_cons+[LNeta]gpaHI) - exp([LNeta]_cons)
   phi_gpaHI:  exp([LNphi]_cons+[LNphi]gpaHI) - exp([LNphi]_cons)
  pEUT_gpaHI:  1/(1+exp([kappa]_cons + [kappa]gpaHI)) - 1/(1+exp([kappa]_cons))

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   eta_gpaHI |  -.3336974   .2525875    -1.32   0.186    -.8287599     .161365
   phi_gpaHI |  -5.150224   8.855219    -0.58   0.561    -22.50613    12.20569
  pEUT_gpaHI |  -.0798361   .1489559    -0.54   0.592    -.3717843    .2121121
------------------------------------------------------------------------------

 ( 1)  [rRDU]gpaHI = 0

           chi2(  1) =    0.05
         Prob > chi2 =    0.8156

 ( 1)  [LNeta]gpaHI = 0
 ( 2)  [LNphi]gpaHI = 0

           chi2(  2) =    7.41
         Prob > chi2 =    0.0246

 ( 1)  [rRDU]gpaHI = 0
 ( 2)  [LNeta]gpaHI = 0
 ( 3)  [LNphi]gpaHI = 0
 ( 4)  [kappa]gpaHI = 0

           chi2(  4) =   21.68
         Prob > chi2 =    0.0002
```

Estimates of the EUT-RDU Mixture Model with All Covariates

```
. ml model lf ML_eut_rdu_prelec2c (rEUT: choiceR $Rdata = $eyes age ) (rRDU: duration $eyes $demog ) (LNeta: duration
$eyes $demog ) (LNphi: duration $eyes $demog ) (kappa: duration $eyes $demog ) (mu: $eyes ) if qid_record==1,
cluster(sid) maximize technique(nr) difficult continue

                                                  Number of obs   =      1,000
```

Wald chi2(0) = .
Log pseudolikelihood = -532.55615 Prob > chi2 = .

(Std. Err. adjusted for 20 clusters in sid)

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
rEUT						
time_prob_pct	.2285527	.4472309	0.51	0.609	-.6480036	1.105109
age	-.0243511	.0283369	-0.86	0.390	-.0798904	.0311882
_cons	1.24885	.8524279	1.47	0.143	-.4218783	2.919578
rRDU						
duration	.0005442	.0109864	0.05	0.960	-.0209888	.0220773
time_prob_pct	-.786981	.6190641	-1.27	0.204	-2.000324	.4263623
female	.0601014	.2267115	0.27	0.791	-.3842449	.5044477
age	.1174018	.0339026	3.46	0.001	.0509539	.1838498
black	-.2240125	.2744073	-0.82	0.414	-.761841	.313816
gpaHI	.1187337	.1524919	0.78	0.436	-.1801449	.4176123
_cons	-2.176109	.807927	-2.69	0.007	-3.759617	-.5926014
LNeta						
duration	.0151815	.0073512	2.07	0.039	.0007734	.0295895
time_prob_pct	1.285891	.3658899	3.51	0.000	.5687595	2.003022
female	.0387006	.2141267	0.18	0.857	-.3809801	.4583813
age	-.0841999	.0181688	-4.63	0.000	-.1198101	-.0485897
black	.0640525	.1708391	0.37	0.708	-.2707861	.3988911
gpaHI	-.2196714	.1158941	-1.90	0.058	-.4468196	.0074768
_cons	1.503196	.416379	3.61	0.000	.6871081	2.319284
LNphi						
duration	.0033219	.015647	0.21	0.832	-.0273457	.0339895
time_prob_pct	.0733387	.4021538	0.18	0.855	-.7148683	.8615457
female	-.0224462	.0960092	-0.23	0.815	-.2106209	.1657284
age	-.235324	.0437836	-5.37	0.000	-.3211383	-.1495096
black	-.209479	.150538	-1.39	0.164	-.504528	.08557
gpaHI	-.2429425	.112502	-2.16	0.031	-.4634425	-.0224426
_cons	4.461215	.967804	4.61	0.000	2.564354	6.358076
kappa						
duration	-.0321199	.0264134	-1.22	0.224	-.0838892	.0196494
time_prob_pct	-.5787758	.7251814	-0.80	0.425	-2.000105	.8425536
female	.1773933	.3853461	0.46	0.645	-.5778712	.9326577
age	.0634234	.0821648	0.77	0.440	-.0976167	.2244635
black	.1451783	.5748008	0.25	0.801	-.9814106	1.271767
gpaHI	.6054713	.4520069	1.34	0.180	-.280446	1.491388
_cons	-1.385882	1.892236	-0.73	0.464	-5.094597	2.322832

```
--------------+----------------------------------------------------------------
mu            |
time_prob_pct |   .0110362    .022576     0.49   0.625    -.0332119    .0552843
        _cons |    .005147   .0081558     0.63   0.528     -.010838    .0211319
-------------------------------------------------------------------------------
```

```
. nlcom (rEUT: [rEUT]_cons) (rRDU: [rRDU]_cons) (eta: exp([LNeta]_b[_cons])) (phi: exp([LNphi]_b[_cons])) (pEUT: 1/(1+exp([kappa]_cons))) (mu: [mu]_cons)

         rEUT:  [rEUT]_cons
         rRDU:  [rRDU]_cons
          eta:  exp([LNeta]_b[_cons])
          phi:  exp([LNphi]_b[_cons])
         pEUT:  1/(1+exp([kappa]_cons))
           mu:  [mu]_cons

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        rEUT |    1.24885   .8524279     1.47   0.143    -.4218783    2.919578
        rRDU |  -2.176109    .807927    -2.69   0.007    -3.759617   -.5926014
         eta |   4.496035   1.872054     2.40   0.016     .8268758    8.165194
         phi |   86.59267   83.80473     1.03   0.301    -77.66158    250.8469
        pEUT |   .7999341   .3028326     2.64   0.008      .206393    1.393475
          mu |    .005147   .0081558     0.63   0.528     -.010838    .0211319
------------------------------------------------------------------------------

rRDU_durat~n:  [rRDU]_cons+[rRDU]duration - [rRDU]_cons
eta_duration:  exp([LNeta]_cons+[LNeta]duration) - exp([LNeta]_cons)
phi_duration:  exp([LNphi]_cons+[LNphi]duration) - exp([LNphi]_cons)
pEUT_durat~n:  1/(1+exp([kappa]_cons + [kappa]duration)) - 1/(1+exp([kappa]_cons))

------------------------------------------------------------------------------
              |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
rRDU_duration |   .0005442   .0109864     0.05   0.960    -.0209888    .0220773
 eta_duration |   .0687771   .0537863     1.28   0.201    -.0366422    .1741964
 phi_duration |   .2881307   1.432984     0.20   0.841    -2.520466    3.096728
pEUT_duration |    .005091   .0071355     0.71   0.476    -.0088944    .0190764
------------------------------------------------------------------------------


 ( 1)  [rRDU]duration = 0

           chi2(  1) =    0.00
         Prob > chi2 =    0.9605

 ( 1)  [LNeta]duration = 0
```

(2)   [LNphi]duration = 0

chi2(2) =   4.61
Prob > chi2 =   0.0999

(1)   [rRDU]duration = 0
(2)   [LNeta]duration = 0
(3)   [LNphi]duration = 0
(4)   [kappa]duration = 0

chi2(4) =   7.78
Prob > chi2 =   0.1000

rEUT_time_~t: [rEUT]_cons+[rEUT]time_prob_pct - [rEUT]_cons
rRDU_time_~t: [rRDU]_cons+[rRDU]time_prob_pct - [rRDU]_cons
eta_time_p~t: exp([LNeta]_cons+[LNeta]time_prob_pct) - exp([LNeta]_cons)
phi_time_p~t: exp([LNphi]_cons+[LNphi]time_prob_pct) - exp([LNphi]_cons)
pEUT_time_~t: 1/(1+exp([kappa]_cons + [kappa]time_prob_pct)) - 1/(1+exp([kappa]_cons))
mu_time_pr~t: [mu]_cons+[mu]time_prob_pct - [mu]_cons

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rEUT_time_prob_pct	.2285527	.4472309	0.51	0.609	-.6480036	1.105109
rRDU_time_prob_pct	-.786981	.6190641	-1.27	0.204	-2.000324	.4263623
eta_time_prob_pct	11.77012	6.291519	1.87	0.061	-.5610314	24.10127
phi_time_prob_pct	6.589264	33.55388	0.20	0.844	-59.17514	72.35367
pEUT_time_prob_pct	.0771021	.1537516	0.50	0.616	-.2242456	.3784498
mu_time_prob_pct	.0110362	.022576	0.49	0.625	-.0332119	.0552843

(1)   [rRDU]time_prob_pct = 0

chi2(1) =   1.62
Prob > chi2 =   0.2036

(1)   [LNeta]time_prob_pct = 0
(2)   [LNphi]time_prob_pct = 0

chi2(2) =   21.03
Prob > chi2 =   0.0000

(1)   [rEUT]time_prob_pct = 0
(2)   [rRDU]time_prob_pct = 0
(3)   [LNeta]time_prob_pct = 0
(4)   [LNphi]time_prob_pct = 0
(5)   [kappa]time_prob_pct = 0

(6) [mu]time_prob_pct = 0

chi2(6) = 132.44
Prob > chi2 = 0.0000

eta_age: exp([LNeta]_cons+[LNeta]age) - exp([LNeta]_cons)
phi_age: exp([LNphi]_cons+[LNphi]age) - exp([LNphi]_cons)
pEUT_age: 1/(1+exp([kappa]_cons + [kappa]age)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eta_age	-.3630661	.2235443	-1.62	0.104	-.8012049	.0750728
phi_age	-18.1572	20.48559	-0.89	0.375	-58.30822	21.99382
pEUT_age	-.0103435	.005519	-1.87	0.061	-.0211607	.0004736

eta_female: exp([LNeta]_cons+[LNeta]female) - exp([LNeta]_cons)
phi_female: exp([LNphi]_cons+[LNphi]female) - exp([LNphi]_cons)
pEUT_female: 1/(1+exp([kappa]_cons + [kappa]female)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eta_female	.1774102	1.002852	0.18	0.860	-1.788143	2.142964
phi_female	-1.922028	9.474494	-0.20	0.839	-20.4917	16.64764
pEUT_female	-.0299026	.0850051	-0.35	0.725	-.1965096	.1367044

(1) [rRDU]female = 0

chi2(1) = 0.07
Prob > chi2 = 0.7909

(1) [LNeta]female = 0
(2) [LNphi]female = 0

chi2(2) = 0.22
Prob > chi2 = 0.8939

(1) [rRDU]female = 0
(2) [LNeta]female = 0
(3) [LNphi]female = 0
(4) [kappa]female = 0

chi2(4) = 2.88
Prob > chi2 = 0.5790

eta_age: exp([LNeta]_cons+[LNeta]age) - exp([LNeta]_cons)
phi_age: exp([LNphi]_cons+[LNphi]age) - exp([LNphi]_cons)
pEUT_age: 1/(1+exp([kappa]_cons + [kappa]age)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eta_age	-.3630661	.2235443	-1.62	0.104	-.8012049	.0750728
phi_age	-18.1572	20.48559	-0.89	0.375	-58.30822	21.99382
pEUT_age	-.0103435	.005519	-1.87	0.061	-.0211607	.0004736

(1) [rDU]age = 0

chi2(1) = 11.99
Prob > chi2 = 0.0005

(1) [LNeta]age = 0
(2) [LNphi]age = 0

chi2(2) = 39.95
Prob > chi2 = 0.0000

(1) [rEUT]age = 0
(2) [rRDU]age = 0
(3) [LNeta]age = 0
(4) [LNphi]age = 0
(5) [kappa]age = 0

chi2(5) = 132.50
Prob > chi2 = 0.0000

eta_black: exp([LNeta]_cons+[LNeta]black) - exp([LNeta]_cons)
phi_black: exp([LNphi]_cons+[LNphi]black) - exp([LNphi]_cons)
pEUT_black: 1/(1+exp([kappa]_cons + [kappa]black)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eta_black	.2974054	.8071462	0.37	0.713	-1.284572	1.879383
phi_black	-16.36544	20.83699	-0.79	0.432	-57.20519	24.47431
pEUT_black	-.0242475	.0944425	-0.26	0.797	-.2093513	.1608563

(1) [rRDU]black = 0

chi2(1) = 0.67
Prob > chi2 = 0.4143

(1) [LNeta]black = 0
(2) [LNphi]black = 0

chi2(2) = 1.94
Prob > chi2 = 0.3790

(1) [rRDU]black = 0
(2) [LNeta]black = 0
(3) [LNphi]black = 0
(4) [kappa]black = 0

chi2(4) = 3.36
Prob > chi2 = 0.4995

eta_gpaHI: exp([LNeta]_cons+[LNeta]gpaHI) - exp([LNeta]_cons)
phi_gpaHI: exp([LNphi]_cons+[LNphi]gpaHI) - exp([LNphi]_cons)
pEUT_gpaHI: 1/(1+exp([kappa]_cons + [kappa]gpaHI)) - 1/(1+exp([kappa]_cons))

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eta_gpaHI	-.8866967	.4413799	-2.01	0.045	-1.751785	-.0216079
phi_gpaHI	-18.6766	18.29074	-1.02	0.307	-54.52578	17.17258
pEUT_gpaHI	-.1141654	.1372874	-0.83	0.406	-.3832437	.154913

(1) [rRDU]gpaHI = 0

chi2(1) = 0.61
Prob > chi2 = 0.4362

(1) [LNeta]gpaHI = 0
(2) [LNphi]gpaHI = 0

chi2(2) = 15.73
Prob > chi2 = 0.0004

(1) [rRDU]gpaHI = 0
(2) [LNeta]gpaHI = 0
(3) [LNphi]gpaHI = 0
(4) [kappa]gpaHI = 0

chi2(4) = 25.49
Prob > chi2 = 0.0000