I Introduction

Experimental economists and decision theorists accept as a "stylized fact" that risk attitudes reflect around a reference point, displaying risk aversion for gains and risk preference for losses[1] This paper investigates one aspect of that stylized fact, the expectation that risk seeking attitudes will be displayed when people are faced with uncertain losses. Our research inquires into how extensive the evidence for it is when decisions are viewed jointly rather than marginally, how robust it is to changes in incentive structures and framing considerations, and how predictable it is by a range of generalized expected utility theories.

We are not merely asking whether risk seeking in the loss domain occurs or is "likely" - the stylized fact summarizes existing experimental evidence (viewed marginally) to answer this question affirmatively. Rather, we ask about the extent that one would expect a given individual to be ***consistently*** risk seeking in their preferences in the face of losses: consistent across both a number of loss situation choices, rather than just one, and consistent across frame changes that affect the ease of processing information about risky choices. To be specific, imagine that the stylized fact warrants an expectation , over and above what one might expect by chance that, in any specific choice between two gambles in the loss domain that are MPSs of one another, a particular individual is likely to display risk seeking attitudes. Given another similar binary choice in the loss domain, would one expect this individual to continue to display risk seeking attitudes ? The expectancy inherent in the stylized fact is ambiguous on this question.

There are two dimensions to the notion of consistency that we explore. The first has to do with the extent, or amount, of risk seeking in the face of loss situations in a given choice environment. For example, a subject in an experiment may be given several binary risky choice situations in a standardized way. If she has risk seeking attitudes in one choice situation is she likely to have those attitudes in the others? The stylized fact interpreted marginally suggests that one expects to see some form of risk seeking in any one of these situations viewed on its own. But is it valid interpreted jointly, across several choice situations, for the same individual?[2]

[1]see Camerer's (1995, p 637) survey article on individual decision making in *The Handbook of Experimental Economics*. The studies of Kagel et al (1990), hereafter KMB, and Harless (1992b) are illustrative of the type of experiments that form the basis for belief in this stylized fact; Camerer (1992,1995) reviews others. See also the seminal article by Kahnemann and Tversky (1979) where prospect theory was developed in part to explain this phenomena.

[2]The issue we are raising here is the consistency of belief in the stylized fact with belief in any one of a number of theories about individual preferences. Theories of choice under uncertainty, when applied to choices in the loss domain, explicitly restrict the preferences, and therefore what we are calling the extent of risk seeking in the loss domain. The "stylized fact" view that risk seeking preferences *in the loss domain* are likely (more likely than by chance) should be carefully interpreted in light of theoretical restrictions and statistical expectations on preferences one accepts when forecasting or predicting experimental choices - this issue is discussed in Section II.

The second dimension of the consistency issue has to do with the amount of risk seeking sustained across different choice environments. Typically in the experiments that substantiate risk seeking preferences in the face of losses, subjects make choices between gambles presented as lists of probabilities and prizes[3] in choice environments which tend to make it costly (in terms of effort) to take an informed, overall view of the binary risks being assessed. For example, in the Kagel et al (1990) and Harless (1992b) experiments, subjects were not explicitly informed, if even they had the analytical skills to comprehend, that the loss-gambles they were choosing between were mean preserving spreads (MPS's) of one another. To be sure, knowledgeable subjects can in principle perform simple calculations to discover this logical fact, but the received view on these "framing" considerations or "accounting equivalences" after years of experimentation (Camerer (1995, p 635), Luce and von Winterfeldt (1994, p 267)[4]. , Slovic, Fischoff, Lichtenstein (1988), Tversky and Kahneman (1988)) is that many experimental subjects do not readily perform such "routine" information processing tasks, even when there are real $ payoffs at stake[5]. Our experiment varies the cost of information processing effort in the choice environment and asks how robust the stylized fact about risk seeking over losses is (whether viewed marginally or jointly with respect to the amount of risk seeking).

Our experimental results, are based on replicating the types of questions studied in Kagel et al (1990), hereafter KMB, and, like their study and others, we find evidence supporting the marginal interpretation of the aspect of the stylized fact we are investigating: namely that, given one specific binary choice situation between two risks in the loss domain, one of which is an MPS of the other, experimental subjects have a predictable tendency to be risk seeking. However, there is little or no evidence for the joint interpretation of the stylized fact, that they are consistently so. Indeed quite the opposite is true: consistent risk aversion is more likely than consistent risk seeking. A brief summary of the questions we asked and the inferences we draw are provided in the table below.

---

[3]Gambles may also be presented as contingent commodities, "actions", rather than as lists of probabilities and prizes,"prospects" (see Harless(1991), Starmer (1992)).

[4]Luce and von Winterfeldt (1994) go as far as to say that the influence of the decision context on the apparent preference between two gambles is one of the most damaging criticisms of subjective expected utility as a descriptive model.

[5]Camerer (1995, p 635) reports results from two experiments (not involving MPSs over losses) suggesting that even when subjects are given help in calculating relevant aspects of some gambles, EU violations are not reduced. On the matter of whether payment induces more or less effort at formal reasoning , he claims that "if [subjects'] preferences are not well formed, it seems unlikely that subjects would be both sophisticated and lazy enough to make an expected utility calculation when they are paid, but not when choices are hypothetical."

	Question	Brief Summary Answer
1	• How consistent is any one individual likely to be in displaying risk seeking attitudes in the loss domain?	*The conventional stylized fact viewed jointly with respect to the amount of risk seeking is reversed for those not subject to framing effects (there is more likely to be frame invariant risk aversion than frame invariant risk seeking) or simply unlikely to happen (there is little correlation between risk attitudes revealed in different frames), even though viewed marginally there is evidence for the stylized fact.*
2	• Is the likely extent of consistency in risk attitudes significantly affected by whether or not subjects are facing hypothetical losses or whether they face real $ losses?	*Explicit financial incentives tend to reduce, but not eliminate, the likelihood of framing effects on risk attitudes when information processing is relatively costly, in terms of effort but have little impact when information processing is easy*
3	• Is there any correlation between making an effort in information processing tasks to recognize "accounting equivalences"[6] (avoid simple framing effects) and general attitudes to risks under uncertainty?	*Sometimes: subjects who act as if [7]they recognize "accounting equivalences" between gambles are more likely to be risk averse than to be risk seeking when financial payoffs are at stake but not when payoffs are hypothetical*
4	• How well can existing theories predict joint risk attitudes within and across different frames? Is predictability in these situations altered at all when explicit financial incentives are at stake?	*Generalized expected utility theories do not predict joint risk attitudes very well, in fact no better and sometimes worse than by chance (appropriately interpreted) except when framing considerations provide for low effort-cost information processing.*

Our answers to these are based on an experiment and on inferences from that experiment using operational subjective statistical methods (Lad(1995)). The following four sections of the paper explain the experimental design and the statistical methodology employed, present the experimental results and statistical inferences that can coherently be made, and assess the predictive ability of a range of Generalized Expected Utility theories. A brief interpretative summary concludes the paper.

---

[6]Luce and vonWinterfeldt (1994)

[7]Our experiment has an operational, behavioural definition of ability to recognize accounting equivalences, according to the extent that a subject is consistent in his/her reported preferences among binary lotteries in partial and full information choice environments (see section II).

II The Experiment

Three of the pairs of gambles used in the KMB experiment were selected for our experiment, as shown in the upper half of Figure II.D. Each of the three binary decision situations, labeled E1, E2, and E3, involves a choice between two gambles with the same mean loss, with the upper right choice being an MPS of the corresponding lower left choice. Subjects[8] were split into two groups, one answering questions only hypothetically, the other facing real $ payoffs[9], and asked to assess their preferences for these gambles in two separate rounds one week apart.

In Round 1 the individual gambles forming part of the binary choice questions for assessment were presented in two frames, first as simple prospects, i.e. lists of probabilities and corresponding prizes, as in Figure II. A (the **standard prospect frame**), and second, as lists of expected wealth levels and probabilities of worst outcomes, as in Figure II. B (the **MPS transparent frame**). We refer to the framing of individual gambles in a binary choice *questions* as the **Q-frame**, and any effect due to a change in the framing of individual questions as a **Q-frame effect**[10]. Figures II A and II B actually present logically equivalent information about two particular gambles, although some effort is required to discover this[11].

Figure II. A: Round 1 questions: the standard prospect frame

Possible outcomes are Best=\$0 loss, Middle=\$14 loss, Worst=\$20 loss	N *gamble label*	M *gamble label*
Probability of \$0 loss	**37%**	**10%**
Probability of \$14 loss	**0%**	**90%**
Probability of \$20 loss	**63%**	**0%**

Figure II. B: Round 1 questions: the MPS transparent frame

Possible outcomes are Best=\$0 loss, Middle=\$14 loss, Worst=\$20 loss	N* *gamble label*	M* *gamble label*
Prob. of worst outcome	**63%**	**0%**
Expected Loss	**\$12.60**	**\$12.60**

The MPS transparent frame makes it immediately apparent that the two gambles have the same mean, and almost immediately apparent that one gamble is a mean preserving spread of the other (there are only 3 outcomes and the probability in one tail is given). Of course, the MPS frame also offers a simple (low effort cost) lexicographic evaluation strategy for assessing gambles: since the gambles are readily seen to have the same expected loss, choose the gamble with the lower probability of a worst

---

[8]The group facing hypothetical payoffs consisted of 19 third year micro economic students at the University of Canterbury. The group facing real $ payoffs consisted of 21 second year micro economic students.

[9]By real $ payoffs we mean that subjects were issued with $25 at the beginning of each round (i.e $50 in total) and told the money was theirs to keep. It was explained (in words and through a demonstration) that, when they had completed the questionnaire for that round, one of the binary choice situations would be chosen at random and their preferred gamble, as recorded in their evaluation booklet/sheet, would be played.

[10]We follow Slovic, Fischoff and Lichtenstein (1988) in characterizing a framing effect as occurring whenever the formulation of choice problems significantly affects behaviour. In particular framing effects occur when people tend to respond to ***explicit*** characteristics in the problem formulation rather than to ***implicit*** or ***underlying*** characteristics (especially if effort or resources have to be used to deduce or infer the latter).

[11]The definition of the mean, the stipulation that probabilities sum to unity, and the assumption that payoffs are fixed and not all equal implies two independent linear restrictions on 4 variables, 3 probabilities and the mean, which imply an underlying 1-1 linear transformation between a mean and any one probability and the other two probabilities.

outcome, here a risk averse choice. The MPS frame can therefore be viewed as a way of simplifying uncertain prospects by focusing on expected returns and “downside risks”. We chose this frame deliberately to see if it would in fact induce risk aversion in situations where past research suggests risk seeking.

During Round 1 each one of the three decision situations E1, E2, and E3 was presented to each subject in each of the two frames in a booklet of 10 pages, one binary choice situation to a page. The pages containing the 6 situation/frame pairings were scrambled with 4 other pages, each of which had one binary choice situation involving not too dissimilar gambles. The overall choice environment in the experimental design of Round 1 neither explicitly encouraged nor discouraged the subjects from comparing different decision situations on different pages, but the booklet form we used (deliberately) increased the effort required to discover the underlying relationships between gambles and gamble pairs across frames. This way of formulating the overall choice *environment* we refer to as an **E-frame**, and any effect on choices due to changing the E-frame as an **E-frame effect**.

In Round 2 of the experiment, held one week after Round 1, we changed the E-frame significantly. Instead of presenting choices in a booklet of 10 pages, we gave each subject a chart like that in Figure II.D. The subjects were then involved in a 3/4 hour discussion (informal, but focused) explaining the unit probability triangle, how the basic gambles could be represented as points in the unit probability triangle, and how pairs of gambles in all of the decision situations were located along iso expected value lines. Mean preserving spreads were discussed in relation to theoretical concepts of risk seeking and risk averse attitudes subjects had met recently in university course work. Q-Framing effects were explained (including explicitly pointing out, with the help of Figure II.D, the induced risk aversion when using the MPS Q-frame). We also discussed briefly in geometric fashion how EU and GEUT theories predict certain patterns of choice in the probability triangle. Subjects were encouraged to ask questions, and did so freely. Moreover, as private information, we explicitly provided them with the answers to their Round 1 assessments on all 3 choice situations, in both Q-frame pairings, in the relevant cells of Figure II.D.

The subjects were then asked to take a second look at the gambles and to choose their more preferred option, in light of their (possibly) new understanding of the decision situations and their previous choices. Clearly the choice environment for Round 2 provides more information, more explicitly, than Round 1’s choice environment. The simultaneous presentation of all gambles on one page, the unification provided by the probability triangle representations of gambles, the explicit calculations of means and geometric representations of MPSs, the explanation and discussion of Q-framing “tricks”, and the explicit presentation of past experience/choices all work in the direction of making it easier (less effort) to sensibly assess risky options. For this reason we call it a **Full Information** (FI) E-frame, while the choice environment for Round 1 is called a **Partial Information** (PI) E-frame.

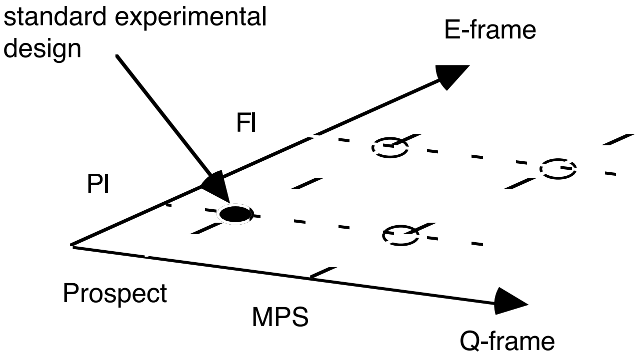
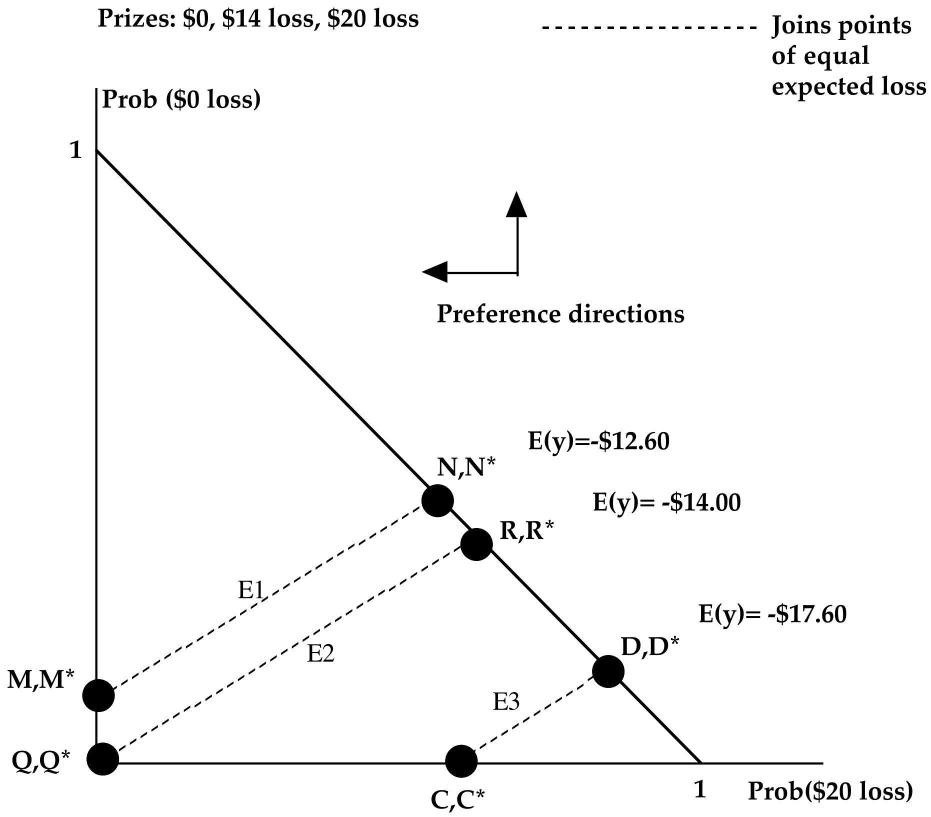


Figure II.C Two dimensional Framing Effects

The framing concept we are using is therefore two dimensional (see Figure II.C). Q-frame effects refer to changes in risk attitudes due to reformulating the presentation of individual gambles in binary choice questions from prospect frame (simple lists of probabilities and prizes) to the MPS transparent frame (a list of possible prizes, mean prize, and the probability of worst outcome), holding constant the choice environment. Similarly, E-frame effects are changes in risk attitudes due to changing from partial information to full information choice environments, holding constant the question format. Q-frame effects can in principle occur in two different E-frame states and E-frame changes can in principle occur with two different states for the Q-frame. Our definitions of the directions for frame changes and corresponding framing effects take the frames chosen in the standard experimental design (prospect Q-frame, partial information E-frame) as a base from which we ask: what happens if we change each type of frame, *ceteris paribus* and *mutatis mutandis*?

Figure II.D: Round 2 : Full Information Frame



Your answers to last week's questionnaire are included in the following table.

Choice pair	Prob of $0 loss	Prob of $14 loss	Prob of $20 loss	Expected $ Loss E(y)
Choice situation between M and N (or M* and N* reframed)				
*M, M**	***10%***	***90%***	***0%***	*E(y)=$12.60 loss*
*N, N**	***37%***	***0%***	***63%***	*E(y)=$12.60 loss*
Choice situation between Q and R (or Q* and R* reframed)				
*Q, Q**	***0%***	***100%***	***0%***	*E(y)=$14.00loss*
*R, R***	***30%***	***0%***	***70%***	*E(y)=$14.00 loss*
Choice situation between C and D (or C* and D* reframed)				
*C, C**	***0%***	***40%***	***60%***	*E(y)=$17.60 loss*
*D, D**	***12%***	***0%***	***88%***	*E(y)=$17.60 loss*

Situation labels in Figure 1	Last week's choice	Choice now ????
M vs N		
M*.vs.N*		
Q vs R		
Q* vs R*		
C vs D		
C* vs D*		

III Statistical Methodology and Theory Specification

The data for an experimental subject "i" is a 12-tuple $\boldsymbol{X}_i = [(E1_{ik}, E2_{ik}, E3_{ik})]$, where $EJ_{ik}= 1$ (risk averting) or 0 (risk seeking) in the three decision situations indexed by "J" and the four possible frame pairs indexed by k (Figure II.C). We use the notation $X_N = \{\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots \boldsymbol{X}_N\}$ to describe a possible sequence of observations of 12-tuples $\boldsymbol{X}_i$ in an experiment involving N subjects. A histogram, $s_k(X_N)$, k=1,2,...R corresponding to any sequence of $X_N = \{\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots \boldsymbol{X}_N\}$ is defined in the natural way as the count of the number of observations $\boldsymbol{X}_i$ in the sequence which lie in each of R categories[12]. The notation $s_1^*, s_2^*, \ldots s_R^*$ denotes the histograms derived from the sequence of actual observations $\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots \boldsymbol{X}_m$ in an experiment with m observations, and $s_1, s_2, \ldots s_R$ denotes category sums for yet to be observed sequences of observations $X_{N-m} = \{\boldsymbol{X}_{m+1}, \boldsymbol{X}_{m+2}, \ldots \boldsymbol{X}_N\}$.

Scientific activity is concerned with making inferences, coherent conditional probability assessments, about yet to be observed sequences of observations $X_{N-m} = \{\boldsymbol{X}_{m+1}, \boldsymbol{X}_{m+2}, \ldots \boldsymbol{X}_N\}$, or their associated histograms $s_1, s_2, \ldots s_R$, having observed other data sequences, summarized by their histograms $s_1^*, s_2^*, \ldots s_R^*$. We base our predictive inferences on equation (1), which has the form of a Polya distribution with parameters $(\alpha_1, \ldots \alpha_R)$. Equation (1) specifies the complete joint predictive probability distribution over events (yet to be observed histograms) we are interested in. It is derived from applying the theory of operational subjective statistical procedures to a fundamental representation theorem of de Finetti on infinitely extendible and exchangeable data sequences (Lad (1993)). Exchangeability in our experimental context means simply that data sequences with the same histograms are regarded as equally likely. The parameters $(\alpha_1, \ldots \alpha_R)$ arise from applying a Dirichlet mixing distribution to a multinomial as outlined briefly in the Appendix.

$$(1)\quad P[s_1, s_2, \ldots s_R \mid s_1^*, s_2^*, \ldots s_R^*] = \frac{(N-m)!}{s_1!s_2!\ldots s_R!} \frac{\Gamma[\sum_{j=1}^{R} \alpha_j + s_j^*] \bullet \prod_{j=1}^{R} \Gamma[\alpha_j + s_j^* + s_j]}{\Gamma[(N-m) + \sum_{j=1}^{R} \alpha_j + s_j^*] \bullet \prod_{j=1}^{R} \Gamma[\alpha_j + s_j^*]}$$

A useful way to think about the choice of parameters $(\alpha_1, \ldots \alpha_R)$ in (1) is to imagine we have no experimental evidence available (m=0),and we wish predict marginally only one trial out in the experiment (N-m=1). In the case equation (1) reduces to

$$(2)\quad P((s1=0),(s2=0),\ldots(sj=1)\ldots(sR=0) \mid 0,0\ldots0) = \frac{\alpha_j}{\sum_{k=1}^{R} \alpha_k}$$

---

[12]The maximum number of categories is equal to 2^{12}=4096, one for each of the logically possible outcomes from the experiment.

which shows that the *relative* sizes of the α_j's indicate the relative ***prior probability*** of an outcome in category j.

As experimental evidence accumulates in the form of histograms (s_1*,s_2*...s_R*), coherent inferences about the next trial of the experiment change. Keeping N-m=1, so predicting out in the future one trial at a time, but having observed the histogram s_1*,s_2*...s_R*, (1) reduces to (3), a multiple category version of Laplace's law of succession for binary outcome events.

(3) $$P((s_1=0)..(s_j=1)...(s_R=0)|\ s_1^*..s_R^*) = \frac{\alpha_j + s_j^*}{\sum_{k=1}^{R} (\alpha_k + s_k^*)}$$

The probability assessments in (3) will be called ***predictive probabilities*** .

Predictive probabilities change with observational data s_k* at a rate determined by the size of the α_j+s_j* and $\sum_{k=1}^{R} (\alpha_k + s_k^*)$. Since $\sum_{k=1}^{R} s_k^* = m$, the number of observations, the larger is $\sum_{k=1}^{R} \alpha_k$ the slower will be the rate of change of predictive probabilities with respect to any given change in observations in category k, s_k*. Consequently $\sum_{k=1}^{R} \alpha_k$ is known as the ***strength*** of belief. Weakly held beliefs change (are updated) rapidly with new data, while beliefs held strongly change less rapidly as new data arises. Alternatively, any given change in beliefs about the likelihood of events requires more observations when beliefs are held strongly as compared to weakly held beliefs. Note that, with these definitions, a predictive probability is a weighted average of a prior probability and the observed relative frequency on the relevant event, with the weights reflecting the strength with which the prior is held relative to the number of observations (m), as in (4).

(4) $$P((s_1=0)..(s_j=1)...(s_R=0)|\ s_1^*..s_R^*) = \ = \frac{\alpha_j}{\sum_{k=1}^{R} \alpha_k}\left(\frac{strength}{strength + m}\right) + \frac{s_j^*}{\sum_{k=1}^{R} s_k^*}\left(\frac{m}{strength + m}\right)$$

Note also that changes in α_k and s_k* in the denominator of (3) have precisely the same (marginal) impact on predictive probabilities. In particular, if $\sum_{k=1}^{R} \alpha_k$, strength of belief, increases by *n* and $\sum_{k=1}^{R} s_k^* = m$, the number of observations, decreases by *n* , the left hand side of (3) remains unchanged. Thus specifying the α_k with a strength of *n* is like saying your prior beliefs are worth (have the same weight in your probability assessments as) *n* observations. Strength of belief can therefore be calibrated in terms of "observational equivalents".

In this paper we restrict our theoretical interest to making inferences "in the small", i.e. about the outcome of **next trial** of the experiment. Theories predict patterns in the data $X_N = \{\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots \boldsymbol{X}_N\}$. For example, EUT predicts an $\boldsymbol{X}_i$ with either all 1's (risk averse), or all 0's (risk seeking),that is, consistent risk attitudes across and within frames for any individual i. There are various families of generalizations of expected utility theory (see Starmer (1992) or Machina (1987) on GEUT theories) which we refer to here as GEUT. GEUT in its Fanning Out (FO) version predicts any one of the patterns $(E1_{ik}, E2_{ik}, E3_{ik}) = (1,1,1), (0,0,0), (1,1,0)$ or $(1,0,0)$ within any specific frame, and, being a frame invariant theory, the same pattern in all frames simultaneously. Similarly Fanning In versions of GEUT predict patterns like $(E1_{ik}, E2_{ik}, E3_{ik}) = (1,1,1), (0,0,0), (0,1,1)$ or $(0,0,1)$ repeated in each frame k[13]. Note that EU is "nested" in GEUT. Frame invariant theories like GEUT make the same predictions independent of the framing of risks. A simple, albeit inelegant, theory that is Q-frame variant is the low effort lexicographic decision strategy induced by the MPS transparent frame. It leads one to predict the risk averse choice pattern (E1,E2,E3)= (1,1,1) in the MPS transparent frame, and equally likely outcomes otherwise. Intuitively, this theory asserts that choices are made by chance except for a "cheap framing trick" due to the experimental design .

No theory predicts perfectly . Deviations from predicted patterns are to be expected. For the purposes of making predictions however we assert four theories to cover a broad range of plausible beliefs about predicted patterns and deviations from them.

1• **EU** places 80% prior probability (equally distributed) on the outcomes predicted by expected utility theory and the remaining 20% probability is spread in inverse proportion to the minimum deviation from an EU pattern.

2• **GEUT** places 80% probability equally on the four patterns consistent with Fanning Out of indifference curves, with the remaining 20% spread in inverse proportion to the minimum number of deviations from an FO pattern[14].

3• **Naive** asserts equal prior probability for any outcome on any one trial of the experiment

4• **FS Naive** (Frame Sensitive Naive) asserts an 80% probability (equally distributed) on patterns of all risk averse choices in the MPS frame with the remaining 20% spread in inverse proportion to the minimum deviations from its' predicted patterns.

[13]Mixed Fan hypotheses are not examined in this current paper.
[14]It turns out that because we are aggregating across locations in the probability triangle that GEUT can also be interpreted as being based on an FI hypothesis rather than a FO hypothesis.

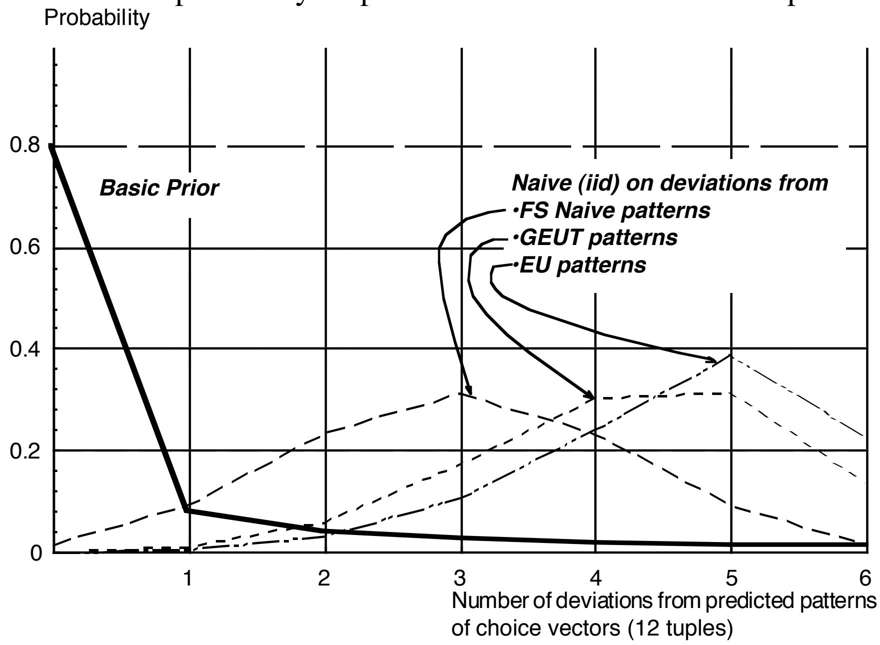
Each theory is assessed for a range of strengths ("observational equivalents") from 1 to 100. Figure III.A illustrates the prior probability being asserted in each theory on the space of the number of deviations from predicted patterns within that theory. By a deviation is meant a difference between a 12-tuple pattern predicted by a theory and the 12-tuple $\boldsymbol{X}_i$ observed. The figure shows the basic idea that theories predict certain patterns (0 deviations) with high prior probabilities and patterns that differ from these theories with lower prior probabilities. For comparison purposes Figure III.A also shows the prior probability distributions of deviations from each of the sets of predicted patterns that one would expect if all 4096 possible 12-tuples were assessed as equally likely.

In our research we are interested in the aggregate amount of frame invariance of risk attitudes. Therefore we examine the predictive power of theories over a space of aggregate frame invariant choices rather than on the simpler space of aggregate deviations. For example, consider a change in the Q-frame from prospect to MPS format holding the E-frame constant. For any one binary question the possible risk attitudes are RARA, RARS, RSRA, RSRS in obvious notation - eg RARS is a **pair** of risk attitudes such that risk aversion (RA) is shown in the "before" (prospect) frame and risk seeking (RS) is shown in the "after" (MPS) frame . Aggregating across the three question pairs we can let RARA be the number of Q-frame invariant risk averse choices, RSRA the number of binary preferences showing risk seeking in the prospect frame and risk aversion in the MPS frame, and so on for RARS and RSRS. Similar definitions apply for E-frame changes. Each of RARA,RARS etc. is a random variable taking on values 0,1,2 or 3, and the sum of these four random variables must be 3, the total number of binary question situations. The realm of possible values for the 4-tuple {RARA, RARS, RSRA, RSRS} along with the prior probabilities assessed under each of our theories is shown in Table III.B.

EU places relatively high prior probabilities on fully frame invariant choices, either 3 RARAs or 3 RSRSs. GEUT includes these patterns but also includes the patterns of 2 RARAs and 1 RSRS and 1 RARA and 2 RRSs[15], albeit with reduced probability. Although each of the theories in pure form is frame invariant, the fact that errors occur creates the possibility of some switching of risk attitudes as frames change purely by chance (as assessed in the prior error distributions). Note the relatively large priors assessed by FS Naive for 2 or 3 RSRA's (rows 2 and 6), 10.6% and 31.9%, respectively, i.e. for being induced to switch from being risk seeking to risk averting with the Q-frame change.

[15]This is why GEUT can be interpreted here as being based on either FO or FI - since each of these theories asserts that out of 3 choices we either have the EU patterns, or patterns with 2 RARAs and 1 RS or patterns with 2 RSRSs and 1 RARA. (see the previous note).

Figure III.A: Prior probability at specified minimum deviation from predicted pattern



x-axis is Minimum deviations from predicted patterns

Table III.B Priors on space of aggregate risk attitudes for Q-frame changes (in %)

	RARA	RARS	RSRA	RSRS		EU	GEUT	FS Naive	Naive
1	*0*	*3*	*0*	*0*		0.10	0.11	0.34	1.56
2	*0*	*0*	*3*	*0*		0.10	0.11	10.60	1.56
3	*0*	*2*	*1*	*0*		0.29	0.34	0.51	4.69
4	*0*	*1*	*2*	*0*		0.29	0.34	1.02	4.69
5	*1*	*2*	*0*	*0*		0.45	0.47	0.51	4.69
6	*1*	*0*	*2*	*0*		0.45	0.47	31.90	4.69
7	*1*	*1*	*1*	*0*		0.90	0.94	2.04	9.38
8	*2*	*0*	*1*	*0*		2.05	1.42	31.90	4.69
9	*2*	*1*	*0*	*0*		2.05	1.42	1.02	4.69
10	*3*	*0*	*0*	*0*	EU, GEUT	42.70	21.40	10.60	1.56
11	*0*	*2*	*0*	*1*		0.45	0.47	1.02	4.69
12	*0*	*0*	*2*	*1*		0.45	0.47	1.02	4.69
13	*0*	*1*	*1*	*1*		0.90	0.94	1.02	9.38
14	*1*	*0*	*1*	*1*		0.58	1.77	2.04	9.38
15	*1*	*1*	*0*	*1*		0.58	1.77	1.02	9.38
16	*2*	*0*	*0*	*1*	GEUT	0.45	21.70	1.02	4.69
17	*0*	*1*	*0*	*2*		2.05	1.42	1.02	4.69
18	*0*	*0*	*1*	*2*		2.05	1.42	0.51	4.69
19	*1*	*0*	*0*	*2*	GEUT	0.45	21.70	0.51	4.69
20	*0*	*0*	*0*	*3*	EU, GEUT	42.70	21.40	0.34	1.56

Further insight into the implications of these theories for the aggregate amount of consistency or switching of risk attitudes is provided by the marginal distributions for the joint distributions specified in Table III.B. Figure III.C plots the various possibilities and Table III.D specifies which general shapes are associated with which theories[16]. Note the wide range of prior marginal probabilities implied by our specification of the error distributions for these aggregates.

Figure III.C General shapes for marginal priors on RARA, RARS, RSRA, or RSRS

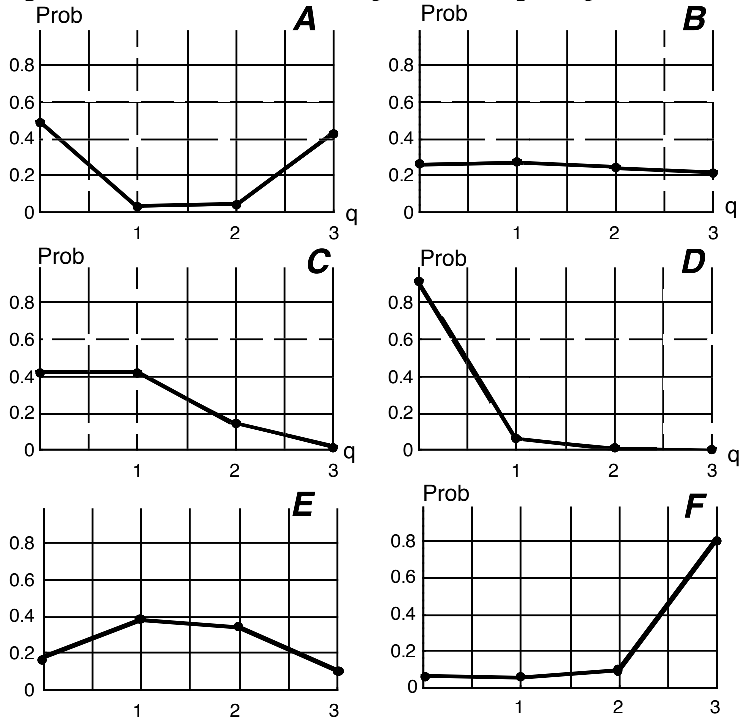


Table III.D Marginal priors for each theory (letter codes from II.F)

	EU	GEUT	FS Naive Δ Q-frame, PI & FI	FS Naive Δ E-frame, mps	FS Naive Δ E-frame,prospect	Naive
RARA	A	B	E	F	C	C
RARS	D[i]	D[ii]	D[iii]	D[iv]	C	C
RSRA	D	D	E	D[v]	C	C
RSRS	A	B	D[vi]	D[vii]	C	C

[16]For example, EU assesses shape A in Figure III.C for the prior marginal distribution on aggregate frame invariant risk aversion (RARA) and for the prior marginal distribution on aggregate frame invariant risk seeking (RSRS), but uses distribution D for the prior on aggregate switching (either RARS or RSRA). The Naive theory, where everything iis viewed as happening by iid chances on the space of 12-tuples, asserts a prior marginal distribution shaped like C for <u>any</u> patterns of risk attitudes - with C the chances of getting 3 choices of the same type of any risk attitude pattern across frames are assessed as very low.

The acid test of a theory is its ability to predict relative to other theories. A systematic way of assessing the predictive performance of theories is provided by the theory of proper scoring rules (Lad (1993, Ch.6)). If an unknown quantity X can take on possible values $\{x_1,...,x_K\}$ a theory can be viewed as asserting knowledge about X in the form of a distribution function $(Q_1,...Q_K)$ from the K−1 dimensional unit simplex where Q_i is the probability of the event $(X=y_i)$. With the convention that $(X=y_i)=1$ if $X=y_i$ and 0 otherwise, the log scoring rule is given by:

$$(4)\quad S(X, Q_1 .. Q_K) = \sum_{i=1}^{K} (X=y_i)*Ln(Q_i)$$

We interpret Equation (4) as the sequential score in the small for a theory's predictive probability distribution at any one point in time. Before the first trial of an experiment a predictive probability assessment $f_x(X_1=x_i)$ is made for the outcome of that first trial X_1 (the prior in standard Bayesian terminology). An outcome y_1 is observed and a score $S_1=Ln(f_x(X_1=y_1))$ calculated. If the theory predicted that outcome with a high probability it gets a high score, otherwise it gets a low score. Since the log of a fraction is negative, the score in this case can be interpreted as a penalty[17]. The predictive probability is then updated via Bayes rule to $f_x(X_2=x_i \mid X_1=y_1)$. The second trial occurs, with outcome y_2 observed and a score $S_2=Ln(f_x(X_2=y_2 \mid X_1=y_1))$ calculated. Continuing in this way the cumulative score for a theory after a sequence of m observations $(y_1,y_2,...y_m)$ is:

$$(4)\quad \begin{aligned} \sum_{i=1}^{m} S_i &= \sum_{i=1}^{m} Ln(f_x(X_i=y_i \mid X_{i-1}=y_{i-1}, X_{i-2}=y_{i-2},...) \\ &= Ln(f_x(X_m=y_m\ , X_{m-1}=y_{m-1},\dots X_1=y_1)) \end{aligned}$$

The second equality holds because the sum of the logs is the log of the product, and the product[18] in this case is just one way of factoring a joint pdf into a product of conditional pdfs. Thus, the log scoring rule has a total score that is independent of the order in which the observations arrive[19], which is particularly appropriate for our purposes.

The magnitudes of average score per prediction in an experiment can be interpreted as a measure of an imaginary or "as if" average unconditional probability of a successful prediction. For example, a

[17]The log function, being increasing and concave, has the property that the penalty increases the less accurate the prediction, both in total and at the margin. Orders of magnitude of scores are -1.6 and -0.11 for probabilities of 20% and 90% respectively.
[18]To assess scores over the entire outcome space. set R, in equation (1) the number of categories, equal to K, the number of possible outcomes, and remove the multinomial coefficient. By exchangeability, all sequences with the same category sum are equally likely. The multinomial coefficient in equation (1) simply counts the number of such sequences.
[19]The log scoring rule is also a proper scoring rule. If an agent asserting a theory $(Q_1,\dots Q_K)$ personally holds $(P_1,\dots P_K)$ as his/her own probability assessments a proper scoring rule assures that the expected score viewed as a function of $(Q_1,\dots Q_K)$, where the expectation is taken with respect to $(P_1,\dots P_K)$, is maximized by choosing $(Q_1,\dots Q_K)$=.$(P_1,\dots P_K)$. A proper scoring rule encourages honest revelation of personal probability assessments if expected scores matter to the agent. See Buehler (1970), Savage (1971) and Lad (1993) Ch. 6

score of –32 over 20 predictions is, on average, -1.6=Log[0.2]. Each observation is being predicted correctly "on average" 20% of the time in the sense that, in retrospect, a sequence of independent marginal assessments of the probability of observed outcomes (a success) each of which is 20% would yield the same Log score as the theory's score of -32.

IV Analysis of Data from the Experiment

IV.A Histograms for joint frame risk attitudes: the joint distribution

Table IV.A presents the histograms for the aggregate joint risk attitudes for each of the two types of framing effects. Each row is a possible pattern of aggregate joint risk attitudes for the four risk attitude changes, RARA, RARS, etc. and each column indicates combinations of frame changes, incentive structures, and the state of the unchanged frame. Columns of relevant proportions of observed outcomes for real $ payoffs and hypothetical payoffs are placed adjacent to one another to facilitate comparisons between experiments with and without explicit financial incentives. The priors for each theory are also presented for reference purposes, since any predictive probability will be a weighted average of the prior and the observed proportion for the relevant event.

Looking across the rows, only row 10, the event of 3 frame invariant *risk averse* choices , stands out in the sense of having positive, and frequently large, observed proportions across both types of framing effects and incentive structures. By way of comparison, row 20, the event of 3 frame invariant *risk seeking* choices, almost always has strictly lower (and never higher) observed proportions than row 10. Thus, given any theory like GEUT or EU that predicts these two patterns with equal prior probability, the predictive chances of frame invariant *risk aversion* will always be higher, often (eg columns 3,4, 6,7,8) significantly higher, than predictive chances of frame invariant *risk seeking* , under either incentive structure. In the real $ payoff experiments (the even numbered columns) comparing row 10 with row 20, anyone asserting GEUT will generally revise *upwards* , from 20% up to as much as 60%, their assessments of the chances of E-frame or Q-frame invariant *risk aversion* and revise *downward* , from 20% down to as low as 5%, their assessments of the chances of frame invariant *risk seeking*. Relatively, the predictive odds ratio could be as high as 5 to 1 in favour of risk aversion over risk seeking. Clearly, sustained (frame invariant) risk seeking is not very likely absolutely and relatively less likely than sustained risk aversion with frame changes that make mean preserving spreads transparent, for either Q-type or E-type frame changes.

An analysis based on a standard (marginal) experimental design (the prospect Q-frame and the partial information E-frame), would arrive at quite different conclusions. Aggregating the relevant data from Table IV.A, one finds that experimentally observed risk attitudes in the prospect Q-frame and partial information E-frame are split about 43% for risk seeking choices more than half the time (2 or 3 such choices out of 3 possible) as compared to about 57% making risk averse choices more than half the time, under either incentive structure. Starting from 50-50 prior chances at either of these events, this evidence, while slightly favouring risk aversion , still suggests a sizeable absolute predictive chance, from 43% to 50%, for risk seeking in the face of losses. Relatively, the predictive odds ratio varies only between 1:1 and 1.4:1 in favour of risk aversion over risk seeking. Comparing these marginal assessments to the predictive probabilities for *frame invariant* risk seeking derived above, marginal analyses tend to substantially <u>*overstate*</u> the case that people will be risk seeking in the face of losses, both in absolute terms and relative to the likelihood of risk aversion. High ***marginally assessed*** predictive chances for risk seeking in the face of losses simply aren't sustainable in the face of frame changes that make mean preserving spreads transparent.

Table IV.A has some further interesting implications. Rows 6 and 8, frame switching events predicted strongly by the simple FS theory, but only weakly by EU and GEUT, also have sizeable proportions in partial information environments, but not in full information environments. This suggests that those who rely on simple framing effects (here, low effort decision strategies) to make their predictions about risk attitudes should revise their assessments of such effects downward in full information choice environments. From the standpoint of experimental design, a full information choice environment can offer some protection against chances of "spurious" results due to frame changes. Switching from always risk seeking to always risk averse (row 2), while not predicted particularly strongly by any of our theories, has significant proportions in 2 cases of hypothetical payoff frame changes, both Q-frame and E-frame, but less so when real $ payoffs are at stake, and not at all in a full information choice environment. Examining rows 2 and 6 together, events where a majority of choices involve switching from risk seeking to risk aversion , observed proportions are high in hypothetical payoff situations for both types of framing effects, but not in real $ payoff situations. GEUT or EU theorists making predictions about the sustainability of risk seeking in the loss domain in the face of either Q-frame or E-frame changes should substantially revise upwards their priors on these events (switching from risk seeking to risk aversion) in hypothetical choice situations, but not be as concerned about them when real $ incentives are at stake.

Looking down the columns of Table IV.A it is clear that, while there is usually a spread of outcomes, many patterns of aggregate joint risk attitudes simply do not show up in the experiment. Choices in aggregate are clearly not purely random (Naive prior). There often appears to be a modal choice pattern or patterns, having high observed proportions, and spreads around these modal patterns of differing amounts. Columns 3 and 4 are of particular interest because they indicate aggregate choice patterns in a full information choice environment, an environment most conducive to rational choice. It is encouraging that, with real $ payoffs (column 4), only around 20% of aggregate choices (row 8, row 14) are outside the general aggregate patterns predicted by GEUT (rows 10,16,19 20). That is. about 80% of observed aggregate choices are consistent with patterns implied by GEUT (albeit not in the same equally distributed manner as our GEUT priors). This general pattern, 80% inside and 20% outside aggregate patterns predicted by GEUT, is also evident with hypothetical payoffs in a full information choice environment, column 3, partially confirming KMB's comment that results in experiments using hypothetical vs real $ payoffs have similar qualitative patterns. However, in partial information choice environments involving a Q-frame change the spread of observed outcomes is much greater (columns 1 and 2 vs columns 3 and 4). For example, with real $ payoffs (column 2) 58% of outcomes in partial information choice environments are outside events predicted by GEUT, and, with hypothetical payoffs, fully 95% of observed aggregate choices are in patterns outside those predicted by GEUT. Clearly the presence of real $ payoffs is reducing the impact of Q-frame effects in partial information environments, but it certainly hasn't eliminated them.

Moreover, the correlation between risk attitudes in a partial information environment in the prospect frame - the standard experimental setup - and risk attitudes in a full information environment is poor. To see this , examine the outcomes of E-frame changes reported in columns 5 and 6 of Table IV.A. In real $ payoff experiments (column 6) about 33% of observed choices involve subjects changing their risk attitudes from those revealed in the standard experimental setup (partial information E-frame, prospect Q-frame) as more explicit information is made available (i.e., their choices lie outside frame invariant rows 10, 16, 19, 20). In hypothetical payoff experiments the comparable figure is 67%. Since prior probabilities for these events are only about 14% for GEUT and EU theories, predictive probabilities for switching risk attitudes must rise, albeit more so when hypothetical payoffs prevail as compared to real $ payoffs . Simply put, as more explicit information about the choice environment is made available relative to the standard experimental setup there is up to a 1 in 3 predictive chance that risk attitudes will change when real $ payoffs are at stake and up to a 2 in 3 chance if payoffs are only hypothetical.

Table IV.A can also be used to uncover correlations between being a careful information processor (E-frame invariant)[20] and risk attitudes. Our inference above that sustained (frame invariant) risk seeking is not very likely absolutely and relatively less likely than sustained risk aversion can be interpreted as claiming that those who are *careful about the processing of information* about risks are more likely to have risk averse attitudes than they are to have risk seeking attitudes. This inference relied on a narrow definition of a sustained risk attitude - the same attitude towards risk is maintained in all binary choice situations in the face of frame changes - a definition which leaves the risk attitudes of those who are not frame invariant undefined. Relaxing the definition slightly to mean maintaining a majority of frame invariant choices of a particular risk attitude, called *usually* risk averse or *usually* risk seeking, permits us to compare the risk attitudes of those who are frame invariant with those who are not frame invariant.

Table IV.B, derived from aggregating the relevant events in Table IV.A, presents the prior and predictive probability distributions for a weakly held GEUT theory over the 3x2=6 possible events of usual risk attitudes (usually risk averse, usually risk seeking, undefined) and interframe consistency in choice (invariant or not) when the choice environment changes from partial to full information in the real $ payoff experiment. As a benchmark, refer to the GEUT prior, which assesses equal chances at being usually risk averse or risk seeking no matter whether a subject is known to be frame invariant or not, although it also assess frame invariance as much more likely than frame variance. There is more likely to be E-frame variance (column 2) than initially predicted (32% observed proportion vs 14% for

[20]Intuitively, frame invariance simply means taking the time and making the effort to examine the available information so as to uncover important underlying relationships, and so avoid simple framing mistakes.

the prior), but given that a subject is E-frame variant, there is no particular bias towards being either risk averse or risk seeking - indeed, chances are that such a subject cannot be classified as usually risk seeking or risk averse in face of E-frame changes. However, given that a subject is E-frame invariant (column 1), it is much more likely that that subject is usually risk averse than usually risk seeking in the face of E-frame changes. Another way to interpret these results is to note that for a given risk attitude (reading the observed proportions across rows of Table IV.E), the predictive odds on a risk averse person being a careful information processor (E-frame invariant) rather than not (between 43:5 and43:3) are much higher than the odds (between 25:5 and 43:3) on a risk seeking person being a careful information processor rather than not.

Intuitively, when real $ payoffs are at stake, subjects who in a partial information environment take care to make choices that are consistent with what they would choose in a full information environment are more likely to be risk averse than to be risk seeking. On the other hand, subjects who are less careful in their processing of information about risks (E-frame variant) are about as equally likely to be either usually risk averse as to be usually risk seeking, if they have any consistent risk attitude at all. Alternatively, risk averse subjects are more likely to be careful information processors than are risk seeking subjects. This correlation of cautiousness in the processing of information about risks and risk attitude did not occur in the hypothetical experiment[21], a result that conflicts with KMB's comment that results in experiments using hypothetical vs real $ payoffs have similar qualitative patterns.

Table IV.B Joint probability distributions on space of Risk Attitudes and E-frame Variance

	Weak GEUT Predictive Probability			GEUT Prior Probability		
	E-Frame Invariant	**E-Frame Variant**	*Totals*	**E-Frame Invariant**	**E-Frame Variant**	*Totals*
usually risk averse	43%	5%	*48%*	43%	3%	*46%*
usually risk seeking	25%	5%	*30%*	43%	3%	*46%*
undefined others	nil	22%	*22%*	nil	8%	*8%*
Totals	*68%*	*32%*	*100%*	*86%*	*14%*	*100%*

[21]The comparable (to Table IV.B) observed proportions for the hypothetical experiment are

	E-Frame Invariant	**E-Frame Variant**
usually risk averse	22%	21%
usually risk seeking	12%	5%
undefined others	nil	40%

Table IV.A Frequency Histograms for aggregate joint risk attitudes (in %)

	Risk Attitudes					Priors				Δ Q-frame: PI		FI		Δ E-frame: Prosp		MPS	
ID	RA RA	RA RS	RS RA	RS RS		EU	GEUT	FS	Naive	Hypo col 1	$ Real col 2	Hypo col 3	$ Real col 4	Hypo col 5	$ Real col 6	Hypo col 7	$ Real col 8
1	0	3	0	0		0.10	0.11	0.34	1.56	•	•	•	•	•	•	5.3	•
2	0	0	3	0		0.10	0.11	10.60	1.56	21	4.8	•	•	16	4.8	•	•
3	0	2	1	0		0.29	0.34	0.51	4.69	•	•	•	•	•	•	•	•
4	0	1	2	0		0.29	0.34	1.02	4.69	•	•	•	•	•	•	•	•
5	1	2	0	0		0.45	0.47	0.51	4.69	•	•	•	•	•	•	11	•
6	1	0	2	0		0.45	0.47	31.90	4.69	16.	24	•	•	11	9.5	•	•
7	1	1	1	0		0.90	0.94	2.04	9.38	5.3	•	•	•	•	•	•	•
8	2	0	1	0		2.05	1.42	31.90	4.69	42	9.5	11	14	21	•	•	9.5
9	2	1	0	0		2.05	1.42	1.02	4.69	•	9.5	•	•	•	4.8	5.3	14
10	3	0	0	0	*	42.70	21.40	10.60	1.56	5.3	24	53	43	5.3	29	63	48
11	0	2	0	1		0.45	0.47	1.02	4.69	•	•	•	•	•	•	•	•
12	0	0	2	1		0.45	0.47	1.02	4.69	•	•	•	•	•	•	•	•
13	0	1	1	1		0.90	0.94	1.02	9.38	5.3	4.8	•	•	•	•	•	4.8
14	1	0	1	1		0.58	1.77	2.04	9.38	•	•	•	4.8	•	9.5	•	4.8
15	1	1	0	1		0.58	1.77	1.02	9.38	5.3	4.8	•	•	16	•	5.3	•
16	2	0	0	1	*	0.45	21.70	1.02	4.69	•	•	5.3	14	16	14	•	•
17	0	1	0	2		2.05	1.42	1.02	4.69	•	•	•	•	5.3	•	5.3	•
18	0	0	1	2		2.05	1.42	0.51	4.69	•	•	•	•	•	4.8	•	4.8
19	1	0	0	2	*	0.45	21.70	0.51	4.69	•	4.8	21	14	5.3	14	5.3	4.8
20	0	0	0	3	*	42.70	21.40	0.34	1.56	•	14	11	9.5	5.3	9.5	•	9.5

Notes for Figure IV.A: * = frame invariant risk patterns predicted strongly by GEUT and/or EU; FI = Full Information Choice Environment; PI = Partial Information Choice Environment; Hypo = Hypothetical payoffs; Real $= real $ payoffs; the experiment with real $ payoffs has 21 subjects; the experiment with hypothetical payoffs has 19 subjects; the change in Q-frame is from prospect to MPS; the change in E-frame is from partial to full information

IV.B Histograms for joint frame risk attitudes: the marginal distributions

Marginal distributions for framing effects are useful for answering questions like those in the introduction: how much frame invariant risk seeking (RSRS) can one expect? How much frame invariant risk aversion (RARA) ? How much frame switching and in which directions (RARS, RSRA)? The frequency histograms for relevant marginals are plotted in Table IV.C along with the marginal prior for GEUT for comparison purposes.

The table is derived from Table IV.A by examining the events RARA, RARS, etc. marginally rather than jointly. For example, RSRS = 2, ie the event of two frame invariant risk seeking choices can arise in 3 ways - rows17,18 and 19 in Table IV.A. Similarly each of the other joint risk attitudes, RARA, RARS, and RSRA can be thought of marginally as a random variable taking on possible values 0,1,2, or 3.

Table IV.C Marginal Histograms and expectations for RARA[22] RARS,RSRA,and RSRS

			Δ Q-frame				Δ E-frame			
			PI Hypo	PI Real $	FI Hypo	FI Real $	Prospect Hypo	Prospect Real $	MPS Hypo	MPS Real $
ID	*GEUT prior*	**RARA**	col 1	col 2	col 3	col 4	col 5	col 6	col 7	col 8
1	*0.27*	**0**	0.26	0.24	0.10	0.09	0.26	0.19	0.11	0.19
2	*0.27*	**1**	0.26	0.33	0.21	0.19	0.32	0.33	0.21	0.09
3	*0.25*	**2**	0.42	0.19	0.16	0.29	0.37	0.19	0.05	0.24
4	*0.21*	**3**	0.06	0.24	0.53	0.43	0.05	0.29	0.63	0.48
5	*1.40*	**mean**	***1.26***	***1.43***	***2.11***	***2.05***	***1.21***	***1.57***	***2.21***	***2.0***
		RARS								
6	*0.918*	**0**	0.84	0.81	1.0	1.0	0.79	0.95	0.68	0.81
7	*0.092*	**1**	0.16	0.19	0	0	0.21	0.05	0.16	0.19
8	*0.013*	**2**	0	0	0	0	0	0	0.11	0
9	*0.001*	**3**	0	0	0	0	0	0	0.05	0
10	*0.097*	**mean**	***0.16***	***0.19***	***0***	***0***	***0.21***	***0.048***	***0.53***	***0.19***
		RSRA								
11	*0.918*	**0**	0.10	0.57	0.89	0.81	0.53	0.71	1.0	0.76
12	*0.092*	**1**	0.53	0.14	0.11	0.19	0.21	0.14	0	0.24
13	*0.013*	**2**	0.16	0.24	0	0	0.10	0.10	0	0
14	*0.001*	**3**	0.21	0.05	0	0	0.16	0.05	0	0
15	*0.097*	**mean**	***1.47***	***0.76***	***0.11***	***0.19***	***0.89***	***0.48***	***0***	***0.24***
		RSRS								
16	*0.27*	**0**	0.89	0.71	0.632	0.57	0.53	0.48	0.84	0.71
17	*0.27*	**1**	0.11	0.10	0.0526	0.19	0.31	0.24	0.05	0.10
18	*0.25*	**2**	0	0.05	0.211	0.14	0.11	0.19	0.11	0.09
19	*0.21*	**3**	0	0.14	0.105	0.09	0.05	0.09	0	0.10
20	*1.40*	**mean**	***0.11***	***0.62***	***0.79***	***0.76***	***0.68***	***0.91***	***0.26***	***0.57***

[22]For presentation purposes all fractions have been rounded to two digits

What inferences can we draw from these marginal distributions? The following points, not all of which are independent, appear to be worth making.

- a The average number of Q-frame invariant risk averse choices exceeds the average number of Q-frame invariant risk seeking choices (compare row 5 for columns 1-4 with row 20). More over, the risk averse (RARA) histograms for Q-frame changes stochastically dominate the risk seeking (RSRS) histograms. Basically Q-frame invariant risk aversion in the loss domain occurs more frequently than Q-frame invariant risk seeking for both partial and full information choice environments and both incentive structures[23]. A GEUT theorist would revise down their prior expectation of joint frame risk seeking (from 1.4 to numbers in row 20 about one half that depending on the strength of their belief) but maintain their expectation about joint frame risk aversion. In a full information environment a GEUT theorist could expect up to 3 times as much frame invariant risk aversion as risk seeking.
- b In the partial information choice environment the mean observed Q-frame invariant choices for both risk averting (RARA) and risk seeking (RSRS) is larger with real $ payoffs than with hypothetical payoffs, (columns 1 and 2, rows 5 and 20) and, the risk seeking histogram from the real $ payoff experiment stochastically dominates the hypothetical payoff histogram. Incentives in the form of $ payoffs therefore tend to induce, on average, more Q-frame invariant risk attitudes, whether risk seeking or risk averting, than do hypothetical payoff structures in a partial information choice environment, and a GEUT theorist would revise their prior expectations of these events accordingly.
- c In the full information choice environment the mean observed Q-frame invariant choices for both RARA and RSRS are very similar across incentive structures (row 5 columns 3,4; row 20, columns 3,4). That is, incentives in the form of $ payoffs make little or no difference to Q-frame invariance in a full information choice environment.
- d In the partial information choice environment the mean observed amount of switching from risk seeking to risk averting (RSRA) is smaller with the $ payoffs than with the hypothetical payoff data (row 15 column 1 and 2), but both observed means are substantially in excess of the prior expectation for this event by GEUT . Incentives in the form of $ payoffs tend to induce less of the Q-framing effect, switching from risk seeking in the prospect frame to risk averting in the mps frame (RSRA), than do hypothetical payoff structures in a partial information choice environment. But incentives do not eliminate this event - indeed a GEUT predictive expectation for RSRA is reassessed from 0.097 to 1.47, depending on the strength of belief and incentive structure.
- e In the full information choice environment the mean observed amount of switching from risk seeking to risk averting (RSRA) is similar with both real $ payoffs and with the hypothetical payoffs (row 15 column 3 and 4); moreover, the observed proportions of no such switching

[23]This result is not surprising since our mps frame induces risk aversion, and in the prospect frame in a partial information environment there is usually a mixture of risk seeking and risk averse choices. However, risk averters also display more E-frame invariance than risk seekers as well.

effects is very high (row 11, columns 3,4) with both incentive structures . In a full information choice environment the “obvious” Q-framing effect of is so unlikely to occur that incentives in the form of $ payoffs make little difference

- f The average number of E-frame invariant risk averse RARA choices exceeds the average number of E-frame invariant risk seeking RSRS choices (compare row 5 for columns 5-8 with row 20). More over, the risk averting (RARA) histograms for E-frame changes stochastically dominate the risk seeking (RSRS) histograms. Thus it is more likely that (using predictive expectations) one will have and keep a risk averse attitude in the face of additional explicit information about choices than it is to have and keep a risk seeking attitude with similar changes to the choice environment. Prior expectations about risk averse attitudes are therefore more robust against changes in the framing of the overall choice environment than are risk seeking attitudes. This suggests that those with risk averse attitudes are also more likely to extract and process relevant information out of partial information environments than those who are risk seeking.
- g In the prospect frame the mean observed E-frame invariant choices for both risk averting (RARA) and risk seeking (RSRS) are larger with the $ payoff than with the hypothetical payoff data (row 5 columns 5,6; row 20, columns 5,6). More over, the risk averse (RARA) histograms for Δ E-frame changes stochastically dominate the risk seeking (RSRS) histograms. Clearly, when the amount and explicitness of relevant information about risks increases subjects will sometimes maintain their risk attitude. Our GEUT has a prior expectation for this to be happening about half the time (1.4 out of max 3) no matter what the incentive structure. Yet a GEUT predictive expectation of such frame invariance occurring is larger when people face real $ payoffs than when they face hypothetical payoffs - apparently the incentives help to motivate subjects to extract and process the underlying information out of the partial information environment. (slightly more so for risk averse subjects (1.57 vs 1.21) than for risk seeking subjects (0.91 vs 0.68)).
- h The mean observed amount of switching from being risk averse to risk seeking(RSRA) with E frame changes exceeds the mean observed amount of consistent risk seeking (RSRS), with hypothetical payoffs (row 15,col 5 vs row 20,col 5). This pattern is reversed when using real $ payoffs (row 15,col 6 vs row 20,col 6). Incentives reduce the amount of switching away from risk seeking towards more consistency in interframe risk attitudes as more explicit information about risks is introduced.

V Log Scores for Predicting Risk Seeking

We now ask how predictable risk attitudes are when there are frame changes. Generally one would expect theories to predict better in full information choice environments where information about risks is easily available and where real $ payoffs are sufficiently high to motivate subjects well. Alternatively, one's intuition is that with hypothetical payoffs, where motivational factors might be low and in partial information choice environments, where the cost of extracting and processing information about risks is high, theories won't predict as well. These types of considerations would lead us to score the predictions of theories along lines suggested in Machina (1987) within given frames and given incentive structures. Some progress is being made along these lines in Macfarlane(1994) and Fountain, McCosker ,Morris(1994).

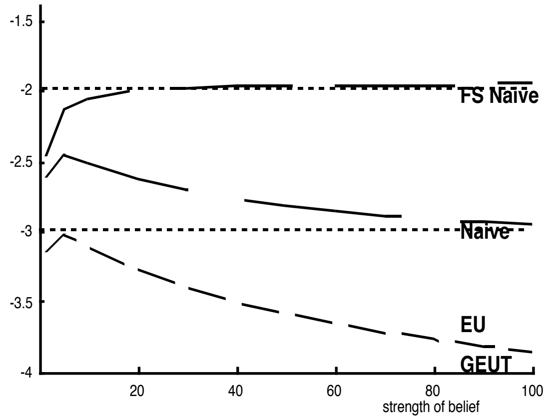
However, real world behaviour (risk attitudes to be explained) occurs in complex changing frames and incentive structures and, while we might expect frame invariant theories to perform poorly in predicting the changes in risk attitudes when frames change, we still can assess theories relative to one another, including whether or not they can predict better than by chance, and investigate how predictions are affected by incentive and framing considerations. Moreover, the histogram of joint risk seeking choices, Table IV.A shows that there is a remarkable amount of E-frame and Q-frame invariance in the aggregate so that there is still some hope for successful prediction - especially since our method of evaluating successful predictions allows theories to "learn" from the data.

First consider predicting Q-frame effects, ie, aggregate amount of change in risk attitudes as the individual question format changes from prospect to mps. Theoretical predictions concerning these effects based on either EU or GEUT do not score particularly well, either absolutely or relatively in partial information choice environments. Examining Figure V.A, average log scores per prediction for EU and GEUT in real $ and hypothetical experiments are at best around -3 (This is equivalent to about a 4% independent success rate per prediction). Under a simple Naive chance theory we found scores of -2.5 per prediction on average (about an 8% success rate). Clearly the Q-frame change from prospect to mps format is creating problems for (basically frame invariant) theories like EU and GEUT. The simple ideas of FS naive concerning "obvious" framing effects predicts better than the alternatives in this partial information choice environment, with scores on average around -2, (a success rate on average of about 14%).

Figure V A, B, C, D average Logscores per prediction for predicting Q-frame effects in various E-frame information environments and incentive structures.

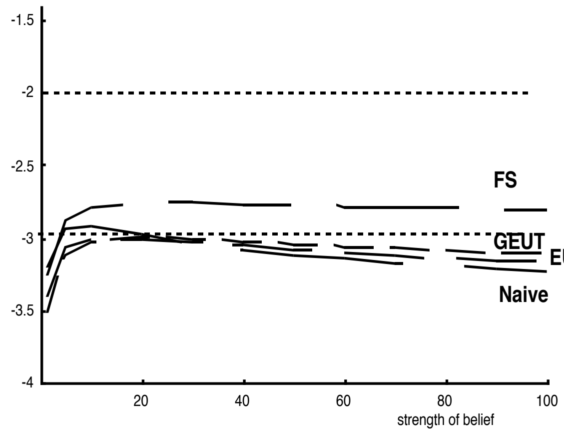
Q-frame effect logscores (PI Hypo)

V.A



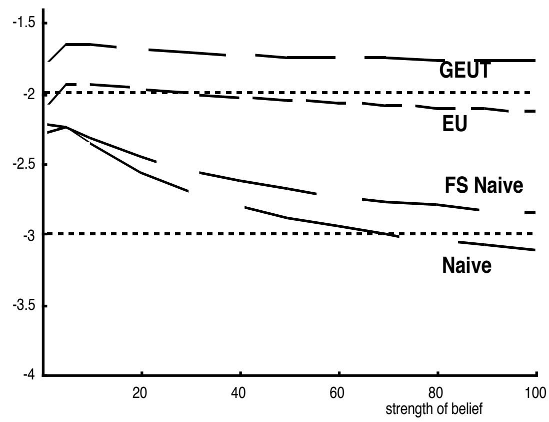
Q-frame effect logscores (PI Real $)

V.B



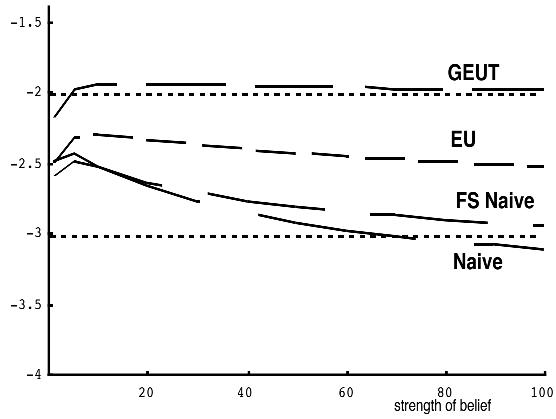
Q-frame effect logscores (FI Hypo)

V.C



Q-frame effect logscores (FI Real $)

V.D



Introducing incentives alters these comparisons significantly. Comparing Fig V A and B, EU and GEUT continue to remain relatively equal to one another, but absolutely their predictive success increases slightly, especially for strongly held versions of the theories. Moreover, they now become on a par with a Naive chance theory absolutely. Further, the gap between their predictive success and the simple FS naive theory's predictions about "obvious" framing effects has decreased. While the FS theory asserts that there are obvious framing effects, and everything else is essentially assessed as identical independent chances, it disperses 40% prior probability for events in rows 2 and 6 in Table IV.A that were never observed in the experiment with real $ payoffs. Thus the scores it received for predicting events like row 8 in Table IV.A that did occur relatively frequently were reduced relative to its scores in the hypothetical payoff experiment where rows 2 and 6 did occur.

In a full information choice environment, Figure V C and D show that relying on the "obvious" framing effect is no longer a successful strategy for prediction. Indeed in such an environment, GEUT has superior predictive success for a wide range of strengths of belief. The best average score of -1.6

(Figure V C) is equivalent to about a 20% average success rate per prediction, much higher than would be expected by Naive chance (scores around -2.5). Notice that the introduction of real $ payoffs (Figure V D vs C) does not affect this conclusion: GEUT is still *relatively* better at predicting than by chance (and better than EU). Paradoxically[24] the absolute scores are slightly worse on average with real $ incentives rather than hypothetical payoffs.

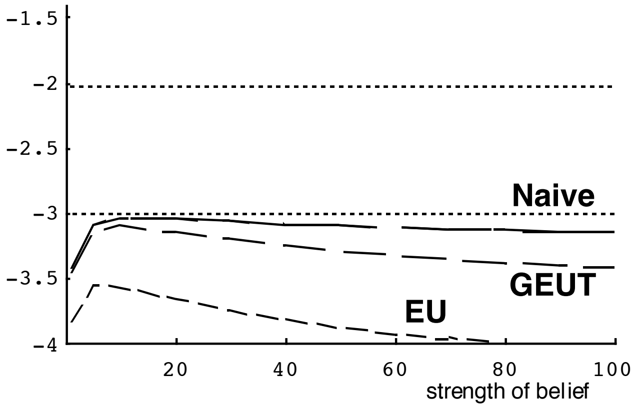
Figure V can also be used to examine the effect that changing the choice environment has on predicting Q-frame effects by reading down rather than across. Comparing A and C in Figure V, the hypothetical payoffs experiment , moving from a partial information to a full information environment increases predictive successes concerning Q-frame effects for theories like GEUT and EU, while simultaneously decreasing the predictive successes of Naive chance theories. When payoffs are in real $ (compare B and D of Figure V) a similar effect is observable - the success of theories like GEUT and EU increases, absolutely and relatively to Naive chance theories, when one moves from a partial to a full information choice environment..

From the evidence available in our experiment, changing incentives alone, at least for the $50 range used in our experiment, does not enable theories like GEUT and EU to predict Q-frame effects any better than by Naive chance, but the combination of real $ payoffs and a full information choice environment does appear to do the trick.. Under such circumstances GEUT does predict the aggregate amount of Q-frame varying choices better than by chance.

Figure V E,F average Logscores per prediction for predicting E-frame effects

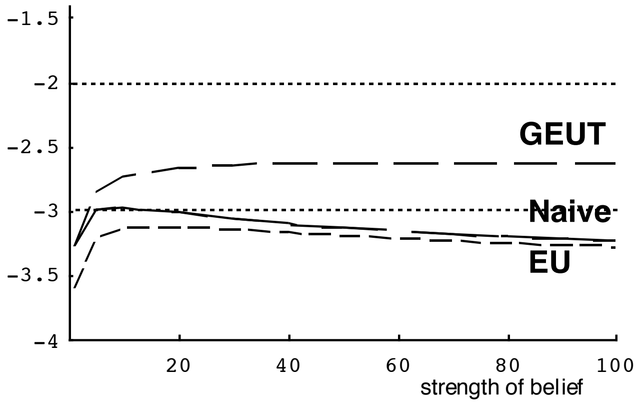
E-frame effect logscores (Prospect Hypo)

V.E



E-frame effect logscores (Prospect Real $)

V.F



Now consider predicting E-frame effects. An E-frame effect is the degree of change (if any) in risk attitudes as the choice environment format changes from one of partial to full information. Once again, theoretical predictions concerning these effects based on either EU or GEUT do not score particularly

[24]The explanation for this lies in the data histogram (Figure IV.A) and the nature of the scoring rule as a criterion of predictive success. Essentially the extra 10% of cases falling into the pattern (3,0,0,0) with the hypothetical data was enough to give it an edge in the scoring procedure.

well. For example best scores of -2.5 on average are still only equivalent to an 8% success rate. In Figure V.E a moderately weakly held GEUT theory predicts E-frame effects about the same as Naive chance. However, when real $ payoffs are at stake at least GEUT predicts E-frame effects better than by Naive chance (Figure V.F). Introducing incentives increases predictive success for E frame effects both absolutely and relatively. Notice in both these cases that neither very weakly held nor very strongly theories score well. In this case, a little theory with a moderate weighting on the data predicts best.

Clearly the E-frame change from partial to full information choice environments is creating problems for (basically frame invariant) theories like EU and GEUT . Subjects are changing their risk attitudes as more and more explicit information becomes available about the overall choice situation, and the theories simply don't predict this well. However, our results show that they are more likely to predict better when their are real $ payoffs at stake as compared to when there are only hypothetical payoffs.

VI Summary

The standard way of presenting gambles in the literature, as lists of prizes and corresponding probabilities in choice environments consisting of sequences of binary choice questions without a unifying framework, can be regarded as choosing frames for experimental subjects from a two dimensional array of possibilities. Experiments incorporating these choices of frames, including our own, indicate a substantial likelihood for risk seeking behaviour in the face of losses. However, when either the individual question format changes (a Q frame change) or the overall choice environment format changes (an E-frame change) in ways that make mean preserving spreads more transparent than they are in the standard experimental design, risk attitudes are likely to change. Our experimental evidence and analysis suggests risk averse attitudes are less likely to change than risk seeking attitudes - indeed, frame invariant risk aversion is much more likely than frame invariant risk seeking when facing losses. Thus, by focusing on one set of experimentally specified frame parameters, and generalizing from this implicit marginal analysis, standard experiments overstate the case for risk seeking in the loss domain.

While it might be argued that our Q-frame change exposes subjects to a cheap framing trick, 'artificially' inducing risk aversion , where exactly is the artificiality? In the induced risk aversion, or in the original risk seeking? Our experimental evidence is clear that after learning about framing tricks of this sort, as well as for E-frame changes, the predictive chances are that risk aversion is more likely than risk seeking for a wide range of prior beliefs. Moreover, the inferences about E-frame changes are significant - since they indicate risk attitudes people are likely to show when they have full and easy access to a wide range of relevant information about risks.

Our analysis suggests that when hypothetical payoff experiments are being used subjects are likely to take the easy way out when they can- i.e. adopt a readily available, reasonable looking (low effort cost) strategy rather than make the effort to discover/formulate their own "true" preferences. This Q-frame variance of risk attitudes is a problem under either of the two incentive structures we examined, although less likely to be a problem when real $ payoffs are at stake in a partial information choice environment, and it virtually disappears in the case of a full information environment no matter what the incentives. E-frame variance, where subjects' risk attitudes change when the cost in effort of creating and processing relevant information about assessing risks decreases, is also more of a problem in hypothetical payoff than in real $ payoff experiments. When real $ payoffs are at stake it is more likely that subjects make the effort in partial information environments to extract the relevant information for their choices than in hypothetical gamble situations. The correlation between choices in these partial and full information situations is far from perfect, however, in either incentive structure .

Neither GEUT nor EU predict the aggregate amounts of frame invariant risk attitudes very well. There is just too much interframe inconsistency, of both types. The revision of frame invariant theoretical beliefs (priors) towards frame dependent predictive probabilities arising in our analysis of predictive joint probabilities sends a clear message: the observational data strongly suggests that frame invariant theories like EU or GEUT need changing to take account of framing effects if they are going to be able to predict risk attitudes better than by chance when frames vary . It is somewhat reassuring, however, that when real $ payoffs are used in experiments, these theories (assuming revision of their predictive probabilities in accord with Bayes rule) do predict aggregate outcomes better than by chance, even after taking account of “obvious” framing effects.

Appendix:

Whatever one thinks about the credibility of expected utility theory, fanning out, risk aversion, framing, etc., we presume that almost everyone would regard the sequence of observations from an experiment like ours involving N subjects, $X_N = \{\boldsymbol{X}_1, \boldsymbol{X}_2 ... \boldsymbol{X}_N\}$, *exchangeably*. Exchangeability is a restriction on one's personal probability assessment of sequences of possible experimental results $X_N = \{\boldsymbol{X}_1, \boldsymbol{X}_2 ... \boldsymbol{X}_N\}$. It means that, if a particular sequence of experimental results $X'_N = \{\boldsymbol{X'}_1, \boldsymbol{X'}_2 ... \boldsymbol{X'}_N\}$ yields a histogram $s_j(X'_N)$ j=1,2,...R, where R is the (finite) number of possible values each $\boldsymbol{X'}_i$ can take, one would assert equal probabilities to <u>any</u> individual sequence of experimental results $\{\boldsymbol{X}_1, \boldsymbol{X}_2 ... \boldsymbol{X}_N\}$ yielding the same histogram. Exchangeability seems eminently sensible in the context of our experiment where there is no information on individual subjects that can be correlated with their individual responses.

Exchangeability has a very powerful implications for coherent personal probability assessments for possible data sequences $X_N = \{\boldsymbol{X}_1, \boldsymbol{X}_2 ... \boldsymbol{X}_N\}$. According to de Finetti's representation theorem, Lad (1993, Ch 5, pp 62-64)[25] , if we regard the sequence $\boldsymbol{X}_1, \boldsymbol{X}_2 ... \boldsymbol{X}_N$ as exchangeable and if our subjective probability distribution is infinitely exchangeably extendible then :

A• The histogram $s_1^*, s_2^*, ... s_R^*$ corresponding to the observed sequence $\boldsymbol{X}_1, \boldsymbol{X}_2, ... \boldsymbol{X}_m$ is a <u>sufficient statistic</u> for any coherent inference about the remaining N-m quantities in the sequence $\boldsymbol{X}_1, \boldsymbol{X}_2 ... \boldsymbol{X}_N$.

B• One's personal probability distribution for an observable sequence $X_n = \{\boldsymbol{X}_1, \boldsymbol{X}_2 ... \boldsymbol{X}_n\}$, for any choice of n observations from N, can be written as a mixture multinomial:

$$\text{(A1)}\quad P[X_1, X_2, ... X_n] = \int_0^1 ... \int_0^1 \prod_{j=1}^{R} \theta_j^{s_j(X_n)} \, d_1 \bullet\bullet\bullet d_{R-1} M(\theta_1 \cdots \theta_{R-1})$$

where $s_j(X_n)$ j=1,2,...R, is the histogram for X_n , $(\theta_1 \cdots \theta_{R-1})$ is a vector of parameters and $M((\theta_1 \cdots \theta_{R-1}))$ is a mixing distribution The parameters θ_j in equation (1) are the imagined "long run" proportions of observations that fall in category j in an infinitely extended sequence of observations X_N.

C• Using the natural conjugate form of mixing function for (A1), a Dirichlet distribution with parameters $(\alpha_1, \alpha_2, ... \alpha_R)$, the <u>conditional</u> distribution of the category sums $s_1, s_2, ... s_R$ for the remaining N-m observations from X_N, given a histogram $s_1^*, s_2^*, ... s_R^*$ of observations on m of them, is distributed Polya(N-m, $\alpha_1 + s_1^*, \alpha_2 + s_2^*, ... \alpha_R + s_R^*$) ; i.e.

$$\text{(A2)}\quad P[s_1, s_2, ... s_R \mid s_1^*, s_2^*, ... s_R^*] = \frac{(N-m)!}{s_1! s_2! ... s_R!} \frac{\Gamma[\sum_{j=1}^{R} \alpha_j + s_j^*] \bullet \prod_{j=1}^{R} \Gamma[\alpha_j + s_j^* + s_j]}{\Gamma[(N-m) + \sum_{j=1}^{R} \alpha_j + s_j^*] \bullet \prod_{j=1}^{R} \Gamma[\alpha_j + s_j^*]}$$

While we presume that almost everyone will regard sequences of observations exchangeably, we are in no way implying that different people will make the same probability assessments for sequences of observations. Equations (A1) and (A2) permit us to distinguish between theoretical views that assess the probability of histograms of data differently through a choice of the mixing distribution M .

[25]This theorem is discussed in Good (1975), Ch. 4 and Diaconis (1977)

Bibliography

Appleby, L. and C. Starmer (1987) “Individual Choice Under Uncertainty: A Review of Experimental Evidence, Past and Present” in Hey and Lambert (1987) 25-45

Bell, David E., Howard Raiffa, and Amos Tversky “Descriptive, Normative, and prescriptive interactions in decision making” in Bell, Raiffa, and Tversky (1988), 9-30

Bell, David E., Howard Raiffa, and Amos Tversky editors (1988), *Decision Making : Descriptive, Normative and Prescriptive Interactions,* Cambridge: Cambridge University Press

Buehler, R. J.(1970) *Measuring Information and Uncertainty* in V. P Godambe and D. A. Sprott editors *Foundations of Statistical Inference* Toronto: Holt Rhinehart & Winston

de Finetti, B (1975) *Theory of Probability* Vol. 2 London: John Wiley

Davis, D.D. and C. A. Holt (1993) *Experimental Economics* Princeton: Princeton University Press

Diaconis, P “Finite Forms of De Finetti’s Theorem on Exchangeability” **Synthese** (1977) 271-281

Good,I. J. (1965) *The Estimation of Probabilities: An Essay on Modern Bayesian Methods*, Research Monograph 30, Massachusetts: M.I.T. Press, August 1968 paperback edition

Fountain, J , M McCosker and D Morris “Are People Really Risk Seeking When Facing Losses?” Discussion Paper 9407 Christchurch: University of Canterbury, Economics Department 1994

Harless, D. (1992a) “Actions versus Prospects” *American Economic Review* Vol 82, 634-650

Harless, D. (1992b) Predictions about indifference curves inside the unit triangle: a test of variants of expected utility theory” *Journal of Economic Behaviour and Organization* 18:391-414

Hey, J. D. (1991) *Experiments in Economics* Oxford: Basil Blackwell

Hey, J.D. and P.J. Lambert, ed. (1987) *Surveys in the Economics of Uncertainty* Oxford: Basil Blackwell

Kagel,J. D. MacDonald, R. Battalio (1990) “Tests of Fanning Out of Indifference Curves: Results from Animals and Human Experiments” *American Economic Review* Vol 80, 912-991

Kahneman, D. and A. Tversky (1979) “Prospect Theory: An analysis of Decision under Risk” *Econometrica*, Vol. 47, 263-291

Kreps,D. M. (1988) *Notes on The Theory of Choice* Westview Press

Lad, F., J.M. Dickey, and M. A Rahman (1990) “The Fundamental Theorem of Prevision” *Statistica*, L, n.1, 19-38

Lad, F (1995) *Operational Subjective Statistical Methods*, Christchurch: University of Canterbury Statistics Department, (mimeo)

Loomes,G. and R Sugden (1982) “Regret Theory: An Alternative Theory of Choice Under Uncertainty” *The Economic Journal* vol. 92, 805-824

Luce, R. D. and D. von Winterfeldt (1994) “What Common Ground Exists for Descriptive, Prescriptive, and Normative Utility Theories?” *Management Science* 40:263-279

Macfarlane, Bruce (1994) "Incentives, Frames and Risk Attitudes in the Loss Domain" Honours Research Project, Economics Department, University of Canterbury, Christchurch, New Zealand

Machina, Mark J.(1987) "Choice Under Uncertainty: Problems Solved and Unsolved" *Economic Perspectives* Summer 1, 121-154

Neilson, W. F. (1992) " A Mixed Fan Hypothesis and its Implications for Behaviour towards Risk" *Journal of Economic Behaviour and Organization* 19, 197-211

Rothschild, M. and J.E. Stiglitz (1970) "Increasing Risk 1: A Definition" *Journal of Economic Theory* 2 225-243

Savage, L.J. (1971) "Elicitation of Personal Probabilities" *Journal of American Statistical Association* 66, 783-801

Slovic, Paul, Baruch Fischhoff, and Sarah Lichtenstein (1988) "Response Mode, Framing, and Information Processing Effects in Risk Assessment" in Bell, Raiffa, and Tversky (1988), 1152-166

Starmer, C. (1992) "Testing New Theories of Choice Under Uncertainty Using the Common Consequence Effect" *Review of Economic Studies* 59, 813-830

Sugden, R (1987) "New Developments in the Theory of Choice Under Uncertainty" in Hey and Lambert (1987) 1-24

Tversky, Amos and Daniel Kahneman (1988) "Rational Choice and the Framing of Decisions" in Bell, Raiffa, and Tversky (1988) 167-192